



Automated karst spring catchment approximation for discharge modelling

Pauline Thinius¹, Felix Joger², Tanja Liesch¹, and Nico Goldscheider¹

¹Karlsruhe Institute of Technology (KIT), Institute of Applied Geosciences, Karlsruhe, Germany

²Federal Institute for Geosciences and Natural Resources (BGR), Berlin, Germany

Correspondence: Pauline Thinius (pauline.thinius@kit.edu)

Abstract. Karst spring discharge modelling is complicated by the limited availability of hydrogeologically delineated catchments, particularly in large-sample applications. We present an automated approach to approximate karst spring catchments from discharge, gridded recharge, and topography and evaluate its suitability for discharge modelling at 63 springs across the wider Alpine region. Recharge-area size is estimated from a simplified water balance and represented by a circular catchment whose position is informed by the topography. The approximations are evaluated against expert-based catchments in terms of geometry and derived model inputs and subsequently applied to discharge modelling with the lumped reservoir model KarstMod and a global long short-term memory (LSTM) network. The estimated recharge areas agree within $\pm 50\%$ of the expert-based delineations for 65 % of the springs, while spatial overlap is more limited (median Intersection over Union: 0.34). Despite this imperfect geometric agreement, the approximations represent catchment-mean elevation, precipitation, and temperature more closely than extracting inputs solely at the spring location. For KarstMod, this translates into substantially improved discharge simulations: approximated and expert-based catchments both achieve a median Kling–Gupta efficiency (KGE) of 0.72, compared with 0.63 for the point-based representation. Differences are particularly pronounced for snow-influenced springs, where representation of catchment elevation affects temperature forcing and simulated snow accumulation and melt. The global LSTM is less sensitive to catchment representation, although greater sensitivity also emerges for snow-influenced springs. These results show that accurate reconstruction of hydrogeological catchment boundaries is not necessarily required to improve model inputs for lumped-parameter modelling. The proposed approximation does not replace expert hydrogeological delineation but provides a scalable, physically informed catchment representation for large-sample karst spring discharge modelling where such delineations are unavailable.

1 Introduction

Approximately 40 % of the Alpine region consist of karstifiable rocks, whose aquifers provide drinking water to major cities such as Vienna and Innsbruck (Goldscheider et al., 2025). Responding rapidly to hydrological events and being strongly influenced by temperature driven snowmelt, karst groundwater systems are especially vulnerable to projected changes in precipitation and snow regimes (Chen et al., 2018). Sustainable management of Alpine karst water resources therefore requires robust, generalisable models applicable across numerous springs.



25 Due to their high individuality and complexity, karst systems are mostly modelled site-specifically, with lumped parameter
 models being widely used (Fan et al., 2023; Rispal et al., 2026; Jeannin et al., 2021; Baudement et al., 2017), since the data
 requirements of distributed models often cannot be met (Hartmann et al., 2014). While the parameters of lumped models
 are usually calibrated rather than derived from physical catchment characteristics (Jeannin et al., 2021), several catchment-
 related assumptions still enter the modelling process: (i) spatially representative catchment precipitation and temperature, (ii)
 30 the elevation distribution, which governs temperature-dependent snow accumulation and melt processes known to strongly
 influence karst spring discharge in both mid-altitude (Rispal et al., 2026) and high-altitude (Chen et al., 2018) mountainous
 systems, and (iii) the size of the recharge area itself. Catchment precipitation illustrates this dependency well: it has been
 derived using station interpolation over the catchment area (Fan et al., 2023; Cinkus et al., 2023; Baudement et al., 2017) or
 catchment-aggregated raster datasets (Rispal et al., 2026), both of which presuppose a known catchment boundary, or from
 35 a single representative station (Jeannin et al., 2021), which instead requires an a priori assumption about which station best
 represents the catchment. Recently, deep learning (DL) approaches — including artificial neural networks (Cinkus et al., 2023),
 transformers (Pölz et al., 2026, 2024), and multi-model ensembles (Zhou and Zhang, 2023) — have emerged as powerful
 alternatives for spring discharge modelling. These approaches require comparatively little a priori knowledge of distributed
 catchment characteristics and have demonstrated a stronger ability to capture non-linearities in karst spring discharge than
 40 reservoir models (Kong-A-Siou et al., 2014). Yet the same dependency on catchment knowledge persists: meteorological inputs
 for these models are similarly derived from a single station (Pölz et al., 2026; Zhou et al., 2024), weighted combinations of
 multiple stations (Cinkus et al., 2023; Kong-A-Siou et al., 2014), or raster data (Wunsch et al., 2022) fed as spatial rather than
 catchment-aggregated input. Global DL models, trained simultaneously on data from multiple stations, have gained increasing
 traction in hydrology (Kratzert et al., 2019c, 2024) and hydrogeology (Liesch and Ohmer, 2026; Ohmer and Liesch, 2026),
 45 and hold similar potential for karst spring discharge prediction across many springs at once, thereby improving generalisability
 under a changing climate. Achieving this generalisation, however, typically requires static catchment features for each station
 — an even stronger dependence on catchment knowledge than in single-spring applications. In the context of surface hydrology,
 topological catchment information in particular has been shown to provide additional predictive value for global LSTMs
 (Kratzert et al., 2019c). Without meaningful static features, models risk using them merely as unique station identifiers rather
 50 than physically informative predictors (Heudorfer et al., 2024, 2025); high-quality, physically meaningful features are therefore
 essential for successful generalisation (Liesch and Ohmer, 2026).

Large-sample approaches, now well established in surface runoff modelling (Kratzert et al., 2018; Heudorfer et al., 2025)
 through the CAMELS family of datasets (e.g., CAMELS-US (Addor et al., 2017), among others), and more recently in ground-
 water level modelling via GEMS-GER (Ohmer et al., 2026), remain rare in karst hydrogeology. This is due, among other
 55 reasons, to the fact that such datasets rely on catchment-aggregated meteorological forcings and static attributes (Addor et al.,
 2017), which in turn presuppose known catchment delineations — precisely the information that is unavailable at scale for
 karst springs since their delineation is far from trivial.

Karst spring catchments are challenging to delineate since they can vary with groundwater level (Ford and Williams, 2007a),
 may include allogenic recharge from adjacent non-karst areas in addition to autogenic karst recharge, and because topographic



60 watersheds do not necessarily align with actual catchment boundaries (Goldscheider, 2010). Tracer tests combined with geo-
 logical and hydrogeological investigations are among the most reliable methods for delineating karst spring catchments (Gold-
 scheider et al., 2008); however, being time- and cost-intensive, they are not a feasible option for large-sample modelling
 approaches. Recently, data-based alternatives have emerged, including spatial correlation analysis between distributed precipi-
 tation and discharge (Longenecker et al., 2017) and sensitivity analysis on 2D convolutional neural networks trained to simulate
 65 discharge from spatial meteorological data (Wunsch et al., 2022), though both approaches still require further refinement be-
 fore operational use. Malard et al. (2015) propose the KARSYS approach, which derives a 3D conceptual model of the karst
 system — including the conduit network and catchment delineation — but requires detailed geological information such as
 the location of aquitards, aquifers, and faults. KARSYS is thus aimed at developing a comprehensive spatial understanding of
 individual systems rather than at rapid catchment delineation for large-scale discharge modelling. Most recently, Seelig et al.
 70 (2024b) presented a method to delineate Alpine karst spring catchments using a lumped-parameter model with a snow routine,
 combined with stable isotope data to identify the most plausible catchment among several candidates; this approach was sub-
 sequently applied to derive a dataset of Austrian spring catchments (Masten et al., 2026). However, the need for expert-based
 delineation of candidate catchments and isotope sampling for each spring limits its scalability to very large samples. As a result,
 most existing applications of karst spring discharge modelling remain focused on individual, well-investigated catchments for
 75 which catchment size and location have been established through previous research (e.g., Rispal et al., 2026; Fan et al., 2023;
 Ollivier et al., 2020), leaving less-investigated karst springs outside the scope of current modelling approaches.

To address this gap, this study targets the following research questions: (i) How can karst spring catchments be approximated
 using a generalisable and automatable approach suitable for large-sample discharge modelling in the wider Alpine region? (ii)
 How well do the approximated catchments represent expert-delineated catchments in terms of size, position and derived me-
 teorological and static input features? (iii) How does catchment representation affect the performance of reservoir models
 80 and global LSTMs in simulating spring discharge? To answer these questions, simple circular catchment approximations are
 derived for 63 karst springs in the wider Alpine region using an automated water-balance- and topography-based approach
 and validated against expert-based delineations. Spring discharge, meteorological forcing, and expert-based reference catch-
 ments for these springs are provided by the newly compiled ALPine hydrographs and catchment Attributes for KArst Springs
 85 (ALPAKAS) dataset (Joger et al., 2026a, b), which incorporates the catchment approximation approach presented here. In a
 second step, spring discharge at the selected sites is modelled using two model types — the reservoir model KarstMod and
 a global LSTM — to assess the influence of the catchment approximation on modelling performance, and thus the suitability
 of the proposed approach for discharge modelling applications. Model performance based on the approximated catchments is
 compared against two benchmarks: (i) models based on the expert-based reference catchments, and (ii) a naive point-based
 90 approach, in which dynamic and static input data are extracted at the spring location rather than aggregated over a catchment.

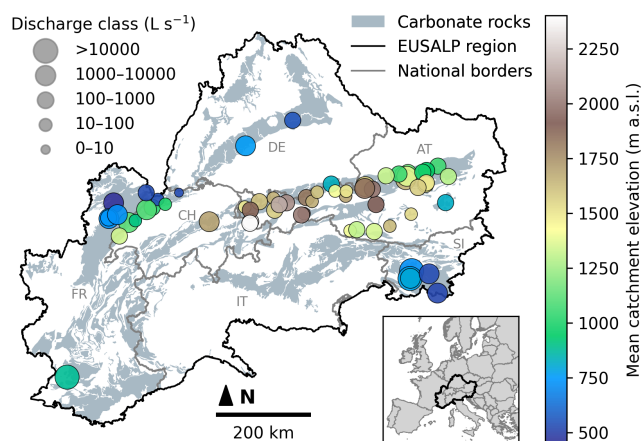


Figure 1. Map showing the location of the 63 selected karst springs in the EUSALP region, with point colour indicating mean catchment elevation and point size indicating mean discharge. The background shows the distribution of carbonate rocks from the Mediterranean Karst Aquifer Map (MEDKAM) (Xanke et al., 2024).

2 Study region and data

2.1 Study region and spring selection

All 63 karst springs considered in this study are located within the European Union Strategy for the Alpine Region (EUSALP) area. They span several major European karst regions: the Northern Calcareous Alps (Austria, and Germany), the Southern Calcareous Alps (Slovenia and Austria), the Folded and Tabular Jura (Switzerland, France), the Swabian and Franconian Alb (Germany), the Provence karst region (France) and the Dinarides (Slovenia).

The springs were selected from the new ALPAKAS dataset (Joger et al., 2026b) based on the following criteria: (i) availability of at least five years of discharge data at daily resolution, (ii) availability of an expert-based catchment delineation, and (iii) a gauging station located close to the spring to minimise the influence of surface runoff on discharge data.

The resulting spring selection covers a wide range of hydro-climatic and physiographic conditions, with mean discharge ranging from 5.1 L s^{-1} for Felsenquelle, a spring used for local water supply in Switzerland, to $24 \text{ m}^3 \text{ s}^{-1}$ for the Ljubljana spring in Slovenia. The smallest catchment in the selected subset covers less than 1 km^2 , whereas the largest extends over 1161 km^2 (Source de la Sorgue). Mean catchment elevations range from 451 m a.s.l. for the catchment of Source d’Arcier in the French Jura to 2400 m a.s.l. for Obwaldquelle in the Central Eastern Alps (Fig. 1).



105 2.2 Data

2.2.1 Reference catchments

Expert-based catchment delineations (hereinafter referred to as reference catchments) used to validate the proposed catchment approximations were obtained from the ALPAKAS dataset (Joger et al., 2026a) and originate from a variety of sources, primarily scientific literature and national or regional environmental agencies. Austrian catchments were delineated using a consistent rainfall–runoff modelling approach combined with isotope data to select the most plausible among several expert-based scenarios (Masten et al., 2026). Catchments in other regions were delineated by experts based on locally available data, which may include tracer tests, geological and tectonic information, and water-balance considerations. Underlying source publications for individual catchments are documented in the ALPAKAS dataset.

2.2.2 Data for catchment approximation

115 Mean discharge for all springs was taken from the ALPAKAS dataset. Meteorological data for the recharge estimation was taken from monthly ERA5-Land reanalysis data for total precipitation, total evaporation, snow depth water equivalent and volumetric soil moisture (accumulated for layer 1 to 4) with a spatial resolution of 0.1° (approximately $8\text{ km} \times 11\text{ km}$) (Muñoz Sabater, 2019). ERA5-Land was selected because it provides a spatially and temporally consistent dataset covering the entire study area and includes all variables required for the recharge estimation, whereas comparable high-resolution national datasets are not available consistently for all variables across all countries. The topographic spring catchments were derived from the Copernicus DEM GLO-30 (ESA, 2022) with 30 m raster resolution.

2.2.3 Data for discharge modelling

For the discharge modelling, discharge data were obtained in daily resolution from the ALPAKAS dataset. Gaps in the time series are not filled in the original dataset to avoid data leakage in deep learning applications and were therefore also not filled in this study. The dataset provides quality-control flags identifying outliers, artefacts, low-quality segments, and changepoint-detected periods, the latter indicating shifts in mean or variance potentially related to changes in measurement conditions (e.g. instrumentation updates). Prior to modelling, flagged observations and periods were filtered from the discharge records. As the ALPAKAS-dataset integrates records from both historical and currently active gauging stations, no common observation period could be defined. Consequently, the selected discharge time series varied in length from 8 to 69 years (mean: 27 years), with the earliest record beginning in 1950.

Meteorological inputs for the reservoir model and the global ANN consisted of daily precipitation and temperature data from national high-resolution gridded datasets. These included RhiresD (MeteoSwiss, 2024a), TabsD (MeteoSwiss, 2024b), TminD (MeteoSwiss, 2024d) and TmaxD (MeteoSwiss, 2024c) for Switzerland, SPARTACUS (GeoSphere Austria, 2020) for Austria, HYRAS (DWD, 2025a, b, c, d) for Germany, SLOCLIM (Škrk et al., 2021) for Slovenia and SAFRAN (Vidal et al., 2010) for France. All datasets have a spatial resolution of approximately $1\text{ km} \times 1\text{ km}$, except SAFRAN, which has a resolution of $8\text{ km} \times$



8 km. For the reference catchments, catchment-aggregated meteorological inputs were obtained directly from the ALPAKAS dataset. For the approximated catchments, the same aggregation procedure as in ALPAKAS was applied to the underlying gridded meteorological datasets using the `exact_extract` function of the `exactextractr` R package (Baston, 2019). For the point representation, meteorological inputs were extracted from the grid cell containing the spring location. Although the underlying interpolation methods differ among these products, high spatial resolution and long observation periods were prioritised over complete dataset homogeneity. This choice was considered appropriate because the study focused on comparing alternative catchment representations for individual springs rather than on direct comparisons between springs. For the global LSTM, a sine curve fitted to the mean daily temperature (T_{sin}) was included as an additional dynamic input, providing an explicit seasonality signal. Following Kong-A-Siou et al. (2014), this variable can be interpreted as an "a priori evapotranspiration" proxy, peaking in summer.

The GLO-30 DEM (ESA, 2022) was again used to derive elevation bands for the KarstMod snow routine. Static catchment descriptors were likewise directly obtained from the ALPAKAS dataset for the reference catchments and derived for the catchment approximations following the same methodology by aggregating the respective spatial datasets over the catchment area (Joger et al., 2026a). For the naive point representation, static attributes were not extracted as true point values but from the grid cell of the respective gridded dataset containing the measurement station. The static attributes comprise catchment location and size as well as topographic, land-use, and hydrogeological characteristics. Only features which are potentially influenced by the catchment approximation were chosen, excluding attributes derived from the discharge time series itself. A complete overview of all static input features and the spatial datasets used for their derivation is provided in Table A1.

3 Methods: Catchment approximation and application to discharge modelling

This study presents a catchment approximation method designed for large-sample karst spring discharge modelling. The proposed approach consists of two steps, illustrated in Fig. 2a. First, the size of the catchment area is estimated using a simple water-balance calculation based on mean annual groundwater recharge and mean spring discharge. Second, a circular catchment of the estimated size is positioned relative to the spring using topographic information derived from a digital elevation model (DEM).

The resulting catchment approximations (C_A) are evaluated in two complementary steps. In **Validation Part I** (Sect. 3.2), the approximations are compared against expert-based reference catchments (C_E), which were delineated using hydrogeological knowledge and site-specific information. Here, performance is assessed based on the ability of the proposed method to reproduce the size, spatial position, and static and dynamic catchment characteristics of the reference catchments. Where applicable, catchment characteristics are additionally compared with those obtained from a naive point representation (C_P), for which characteristics are extracted at the spring location. In **Validation Part II** (Sect. 3.3), the practical relevance of the approximated catchments is assessed by using them as input for spring discharge modelling with two data-driven approaches: the conceptual reservoir model KarstMod and a global Long Short-Term Memory (LSTM) network. Model performance based on C_A is compared against two benchmarks, for which dynamic and static inputs are derived from (i) C_E and (ii) C_P , respectively.

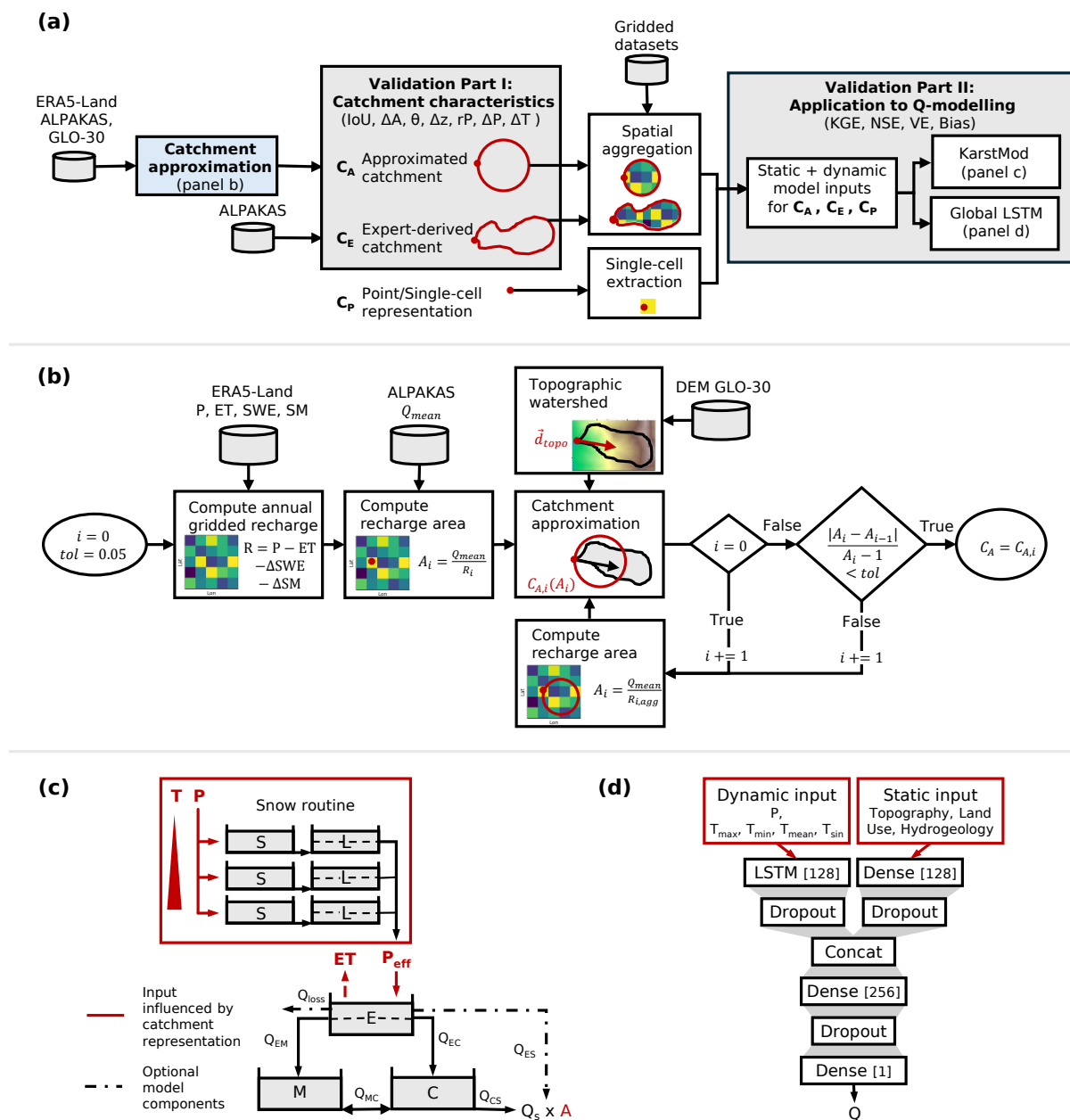


Figure 2. (a) Flow diagram of the overall study setup. (b) Detailed flow diagram of the iterative catchment approximation method. (c) Schematic overview of the KarstMod model and (d) the global LSTM architecture, with parameters and inputs affected by the choice of catchment representation highlighted in red in both panels. All abbreviations are explained in the text.



3.1 Catchment approximation

170 3.1.1 Estimate of recharge area size

Assuming long-term steady-state conditions, the water balance of a spring and its contributing catchment can be expressed as

$$Q = R \cdot A \quad , \quad (1)$$

where Q is the mean annual spring discharge, R is the mean annual recharge and A the catchment area that contributes to the water balance (Goldscheider, 2010). Rearranging yields an estimate of the recharge area A . This formulation assumes
 175 that the long-term water balance is represented by recharge and discharge at the considered spring and therefore neglects groundwater exchange with neighbouring aquifers, deep regional flow, and discharge through additional or overflow springs. The implications of these assumptions for recharge-area estimation are discussed in Sect. 6.1. Mean annual recharge (R) was estimated from monthly ERA5-Land data described in Sect. 2.2.2, following the general approach of Goldscheider et al. (2025). Monthly recharge was calculated as

$$180 \quad R = P - AET - \frac{dS}{dt} - \frac{dSWE}{dt} \quad , \quad (2)$$

where P is precipitation, AET is actual evapotranspiration, S is soil water storage, and SWE is snow water equivalent. Surface runoff was assumed negligible due to the generally high infiltration capacities of karst terrains (Hartmann et al., 2015; Wan et al., 2024). Monthly recharge values were aggregated to annual totals for each hydrological year (1 October-30 September, following the convention commonly used in Austria and Switzerland, as it generally captures a complete snow
 185 accumulation and melt cycle also for higher-elevation catchments in the Alps) and subsequently averaged to obtain long-term mean annual recharge. To ensure consistency between recharge and discharge estimates, only hydrological years with corresponding discharge observations were included in the calculation.

3.1.2 Positioning and shape of the catchment approximation

The recharge area of a spring is situated above the spring elevation (Goldscheider, 2010), providing a topographic constraint on
 190 its potential spatial extent. Topography is therefore used as an readily available proxy for the orientation of the recharge area, enabling a fully automated approximation without requiring site-specific hydrogeological information. However, topographic and karst groundwater divides do not necessarily coincide (Ford and Williams, 2007a), and the limitations of using topography as a proxy for recharge-area orientation are discussed in Sect. 6.1.2. To determine the position of the approximated catchment, first, topographic watersheds were delineated using the Whitebox library (Wu and Brown, 2025; Lindsay, 2016) in R and
 195 the Copernicus DEM GLO-30. Prior to watershed delineation, depressions were filled and artificial barriers were breached to ensure continuous flow routing. Flow directions and flow accumulation were then derived using the D8 algorithm. Cells with a flow accumulation of at least 1000 DEM cells were initially classified as stream cells.

Because gauging station locations frequently do not coincide with DEM-derived stream cells (Lindsay et al., 2008), Jenson's snapping method was used to relocate each station to the nearest stream cell within a maximum search distance of 180m. For



200 karst springs located close to higher-order streams, this procedure may result in snapping to an inappropriate channel and subsequent delineation of an unrealistically large watershed relative to the recharge area estimated from the water balance. Therefore, the plausibility of the snapped location was evaluated against the expected recharge-area-size and, where necessary, the stream network and snapping procedure were iteratively refined (Appendix B).

The resulting topographic catchment was used to derive the vector $\mathbf{d}_{\text{topo}}$ connecting the spring location and the centroid of
 205 the topographic watershed. This vector was assumed to represent the dominant orientation of the recharge area relative to the spring.

The approximated catchment was represented in a simplified form as a circle, with the area estimated from the water balance (Sect. 3.1.1), initially centred on the spring location. The circular shape was chosen as the simplest representation that preserves the estimated area without introducing additional assumptions about catchment geometry, which can be highly irregular in
 210 karst systems. The circle was subsequently translated along $\mathbf{d}_{\text{topo}}$ until the spring location coincided with its boundary. This configuration reflects the assumption that the spring is situated near the downgradient margin of its contributing recharge area, while the recharge occurs upslope in the direction indicated by the topographic watershed.

3.1.3 Iterative refinement of catchment approximation

Although recharge heterogeneity is partly smoothed by the relatively coarse spatial resolution of the ERA5-Land dataset, a
 215 single grid cell may still not adequately represent the spatial variability of recharge within larger catchments. To account for this effect, the catchment approximation was iteratively refined (Fig. 2b).

In the initial step ($i = 0$), recharge was extracted solely from the ERA5-Land grid cell containing the spring. This recharge estimate was used to calculate the recharge area A_0 , from which the initial circular catchment approximation $C_{A,0}$ was derived and positioned according to the direction vector $\mathbf{d}_{\text{topo}}$ obtained from the topographic catchment.

220 For subsequent iterations ($i \geq 1$), mean recharge was calculated by spatially aggregating recharge over the previously estimated catchment $C_{A,i-1}$. The updated recharge estimate was then used to recalculate the recharge area A_i and generate a new catchment approximation $C_{A,i}$. This procedure was repeated until the relative change in estimated catchment area between two consecutive iterations was less than 5 %:

$$\frac{|A_i - A_{i-1}|}{A_{i-1}} < 0.05 \quad . \quad (3)$$

225 3.2 Validation Part I: Geometry, static and dynamic catchment characteristics

The geometric agreement of the catchment approximations with the expert-based delineations was assessed using three metrics. The percentage over- or underestimation of the catchment area was defined as

$$\Delta A = 100\% \times \frac{A(C_A) - A(C_E)}{A(C_E)} \quad , \quad (4)$$

where $A(C_E)$ is the area of the C_E , and $A(C_A)$ is the area of the corresponding approximation C_A . Positive values indicate
 230 an overestimation of the catchment area by C_A relative to C_E , and negative values an underestimation.



To assess the directional agreement, the angle θ between the vectors connecting the spring to the centroids of the approximated and expert-based catchments was computed (Fig. D1a). An angle of 0° indicates perfect agreement in orientation, whereas 180° indicates opposite alignment.

The overall spatial agreement between the two catchments was quantified using the Intersection over Union (IoU), a metric commonly applied in object detection, defined as

$$IoU = \frac{|C_A \cap C_E|}{|C_A \cup C_E|}, \quad (5)$$

where the intersection and union of both geometries are illustrated in Fig. D1b. An IoU of 0 indicates no spatial overlap, whereas a value of 1 corresponds to perfect agreement between the two catchment delineations.

In addition to geometric agreement, the most important static and dynamic catchment features for discharge modelling were compared, this time also including the naive point representation (C_P). Because elevation strongly influences the snow routine, differences in the elevation distribution were evaluated by comparing the mean elevation ($\bar{z}$) of C_A and C_P against C_E , and by computing the elevation bias $\Delta\bar{z} = \bar{z}(C_A) - \bar{z}(C_E)$ (and analogously for C_P). To assess how the representation affects the most influential meteorological driver of discharge, the Pearson correlation (r_P) between the daily catchment-averaged precipitation series of C_E and C_A , and of C_E and C_P , was used as an indicator of timing errors, while the difference in annual precipitation sum (ΔP) quantified the effect on the total water available to the model. Finally, because temperature governs snow and ice melt processes, the temperature bias ($\Delta\bar{T}$) of C_E and C_A , and C_E and C_P , respectively, was computed. All difference metrics (ΔA , $\Delta\bar{z}$, ΔP and $\Delta\bar{T}$) are reported as approximation minus reference, so that positive values indicate an overestimation relative to C_E . To ensure consistency with the discharge modelling, the meteorological indicators were computed only for hydrological years with $\geq 80\%$ availability of observed discharge, i.e. the same years that enter the discharge modelling.

3.3 Validation Part II: Application to discharge modelling

3.3.1 Reservoir model KarstMod

KarstMod is a conceptual discharge modelling platform specifically developed for karst systems, allowing representation of both rapid conduit flow and slower matrix flow components (Mazzilli et al., 2019; Sivelles et al., 2025). In this study, version 3.0.11 was used.

Daily precipitation (P), air temperature (T), and potential evapotranspiration (PET) constitute the meteorological model inputs. PET was calculated prior to model execution following the approach of Oudin et al. (2005) based on daily temperature and latitude. Prior to entering the hydrological model, precipitation is transformed into effective precipitation (P_{eff}) by the snow routine described below. P_{eff} and PET are transformed through a succession of serial and parallel reservoirs representing the unsaturated and saturated zone of the karst system to simulate spring discharge (Q_S).

The model structure consists of an upper infiltration reservoir (E) and up to three saturated-zone reservoirs (M, C, and L), which represent different groundwater storage and flow components (Fig. 2c). Reservoir E distributes water to the lower reservoirs M, C and L. To limit model complexity while retaining the ability to represent both fast conduit and slow matrix



flow pathways, only configurations containing the epikarst (infiltration) reservoir E, the matrix reservoir M, and the conduit reservoir C were considered in this study. The flux Q_{MC} between reservoirs M and C can reverse direction depending on the water-level difference between the two reservoirs, representing bidirectional matrix-conduit interaction (Mazzilli et al., 2019).

Optionally, a loss flux (Q_{loss}), representing overflow springs, and a direct and fast recharge pathway from the infiltration reservoir E to the spring (Q_{ES}) can be enabled. Both fluxes are only activated when the level in reservoir E exceeds thresholds h_{loss} and h_{ES} , respectively. Reservoir E is further characterised by a negative lower storage bound h_{min} , representing water that remains available for evapotranspiration but does not contribute to groundwater recharge.

Each reservoir is assigned a recession coefficient k , which determines its outflow, e.g. for the outflow of reservoir E to the spring:

$$Q_{ES} = k_{ES} \cdot h_E \quad , \quad (6)$$

where h_E designates the water level in reservoir E.

Only the conduit reservoir C—and, when enabled, the direct flux Q_{ES} from reservoir E—contribute to final spring discharge, consistent with the conceptual view of karst systems as underground river networks draining to a terminal spring (Ford and Williams, 2007b). Total spring discharge (Q_S) is therefore obtained as the sum of these two contributions, scaled by the recharge area A :

$$Q_S = A \cdot (Q_{CS} + Q_{ES}) \quad . \quad (7)$$

The snow routine implemented in KarstMod is based on the HBV snow module and represents the snowpack using two conceptual reservoirs: a solid snow reservoir (S_S) and a liquid water reservoir (S_L) (Sivelle et al., 2025). Precipitation is added to S_S when air temperature is at or below a threshold temperature (T_{thr}), and otherwise to S_L . When $T > T_{\text{thr}}$, snowmelt is simulated using a degree-day approach:

$$m(t) = MF \cdot (T(t) - T_{\text{thr}}) \quad , \quad (8)$$

where $m(t)$ is the melt rate and MF is the melt factor. Meltwater is transferred to the liquid water reservoir. The snowpack can retain liquid water up to a water-holding capacity (CWH), which was set to 0.1, corresponding to 10 % of the snow water equivalent of the solid snowpack. Excess liquid water contributes to runoff as effective precipitation (P_{eff}). Although KarstMod includes a refreezing routine, this process was neglected because previous studies reported only minor effects on hydrological model performance (Magnusson et al., 2014; Girons Lopez et al., 2020). To account for elevation-dependent snow processes, each catchment was divided into 100 m elevation bands. Air temperature in each band was adjusted using a constant lapse rate of $-0.6^\circ\text{C}(100\text{m})^{-1}$ relative to the mean catchment elevation. Snow accumulation and melt were simulated separately for each band and aggregated using area weighting to obtain catchment-scale effective precipitation (P_{eff}), which recharges the epikarst reservoir (E).

For each spring, eight configurations of the model were tested, differing on whether (i) a loss flux (Q_{loss}) was included, (ii) the direct flow path from reservoir E to the spring (Q_{ES}) was activated, and (iii) evapotranspiration (ET) was considered. ET



Table 1. KarstMod parameters and calibration ranges, indicating the model configurations in which each parameter is active.

Parameter	Description	Calibration range		Unit	Active when
		Lower	Upper		
RA	Recharge area	$0.95 \times A^a$	$1.05 \times A^a$	km^2	All
$h_{\min}(E)$	Minimum water level in reservoir E	-50	0	mm	ET
k_{EC}	Recession coefficient between reservoir E and C	0.001	3	d^{-1}	All
k_{EM}	Recession coefficient between reservoir E and M	0.001	1	d^{-1}	All
k_{MC}	Recession coefficient between reservoir M and C	0.001	1	d^{-1}	All
k_{CS}	Recession coefficient between reservoir C and S	0.01	3	d^{-1}	All
T_{thr}	Threshold temperature for snow melt	-1	1	$^{\circ}\text{C}$	All
MF	Melt factor	0.5	6	$\text{mm d}^{-1} ^{\circ}\text{C}^{-1}$	All
$h_{ES}(E)$	Threshold for activation of Q_{ES}	0	100	mm	Q_{ES}
k_{ES}	Recession coefficient between reservoir E and spring	0.01	1	d^{-1}	Q_{ES}
$h_{\text{loss}}(E)$	Threshold for activation of Q_{loss}	0	150	mm	Q_{loss}
k_{loss}	Recession coefficient for outflow towards overflow spring	0.001	1	d^{-1}	Q_{loss}

^a For C_E , A corresponds to the area of the reference catchment; for C_A and C_P , it corresponds to the recharge area estimated using the water-balance approach presented in Sect. 3.1.

was optionally neglected to account for the highly permeable nature of karst systems, in which infiltration is rapid and soil water storage is limited — particularly in high-elevation catchments, where vegetation cover and evapotranspiration demand are comparatively low (Malard et al., 2016). All optional model components are dashed in the model overview in Fig. 2c.

Each of the eight configurations was calibrated separately using the pseudo-Monte Carlo calibration procedure implemented in KarstMod, which employs Sobol sequences for parameter sampling. Depending on the configuration, between eight and twelve parameters were calibrated, with parameter ranges given in Table 1. The recharge area parameter (RA) was constrained to vary within $\pm 5\%$ of the size of the respective catchment representation. Calibration was performed using the Kling–Gupta efficiency (Gupta et al., 2009) of the square-root-transformed discharge ($\text{KGE}\sqrt{Q}$) as the objective function. The best-performing configuration was selected based on calibration performance. To account for equifinality (Beven and Binley, 1992), the final prediction was obtained as the median of the 40 best-performing parameter sets of the selected configuration.

3.3.2 Global LSTM

A global LSTM (Hochreiter and Schmidhuber, 1997) was used as a second modelling approach to evaluate the derived catchment approximations. LSTMs are a type of recurrent neural network capable of learning long-term dependencies in sequential data, a property that makes them well suited to time series modelling in hydrology (Kratzert et al., 2021). Rather than training a separate model for each spring, a single model was trained jointly on the dynamic meteorological time series of all catchments, following the global modelling approach of Kratzert et al. (2019b) and the specific architecture of Liesch and Ohmer (2026).

The model architecture consists of two processing branches. The dynamic branch processes daily meteorological inputs using a single-layer LSTM with 128 hidden units and a sequence length of 120 days, such that each discharge prediction



is conditioned on the preceding 120 days of meteorological observations. The static branch processes catchment attributes through a fully connected dense layer with 128 units and ReLU activation. Dynamic inputs were standardised separately for each catchment to zero mean and unit variance using training-period statistics, while static inputs were normalised to $[-1, 1]$ across all catchments. A dropout layer (rate = 0.3) follows each branch to reduce overfitting. The final hidden state of the dynamic branch's LSTM is concatenated with the output of the static branch and passed through a dense layer with 256 units, followed by a single-neuron output layer producing a daily discharge estimate in a sequence-to-value ("seq2val") configuration. Processing static and dynamic inputs separately in this way is computationally more efficient, more stable, and less memory-intensive than the alternative "repetition" approach, in which static features are repeated at every time step and concatenated with the dynamic inputs (Liesch and Ohmer, 2026).

The model was trained by minimizing the mean squared error (MSE) loss using the Adam optimiser, with a batch size of 256 for a maximum of 20 epochs. A learning rate scheduler linearly ramped the learning rate up to a target of 0.001 during training, and early stopping (patience of 5 epochs, based on validation loss) was used to prevent overfitting. To account for stochastic variability from random weight initialisation, each LSTM variant was trained with 10 random seeds, and the median discharge simulation across the resulting ensemble was used to compute the reported performance metrics.

3.3.3 Experimental design

Model experiments were conducted with KarstMod and the global LSTM using three catchment representations (C_E , C_A , and C_P). For the LSTM, two sets of static features were considered. Environmental static features (*Env*) were derived from the respective catchment representations, whereas random static features (*Rand*) of identical dimensionality were independently sampled from a uniform distribution between -1 and 1 . The same random feature vector was assigned to each spring across all three catchment representations, allowing differences among LSTM-Rand models to be attributed solely to differences in the dynamic meteorological inputs.

Combining the three model setups (KM, LSTM-Env, and LSTM-Rand) with the three catchment representations resulted in nine model-catchment combinations, denoted by model setup and catchment representation (e.g., KM- C_E and LSTM-Env- C_A). For C_E and C_A , meteorological inputs and static attributes were derived by spatial aggregation over the respective catchment polygons. For C_P , inputs were derived at the spring location, except for the recharge area required by KarstMod, for which the water-balance-derived area of the corresponding C_A was used.

Due to differences in data availability among the spring discharge records, a common training, validation, and testing period could not be defined. Instead, the final two years of each time series were reserved as an independent test period. For the global LSTM, an additional two-year validation period preceding the test period was used for early stopping and hyperparameter selection. The remaining data were used for model training. For KarstMod, the discharge observations preceding the test period were used for calibration. To reduce the influence of initial reservoir conditions, the forcing data were extended by an additional five years prior to the calibration period for model warm-up (Mazzilli et al., 2019); no discharge observations from this period were used for calibration. An overview of the data split for each spring is given in Table C1.



Model performance was assessed for the independent test period using five complementary metrics: the Kling-Gupta efficiency (KGE) (Gupta et al., 2009), the Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970), the Pearson correlation coefficient (r) as a measure of timing accuracy, the relative bias (rBias), and the volumetric efficiency (VE) (Criss and Winston, 2008). The relative bias is defined as

$$350 \quad \text{rBias} = \frac{\overline{Q_{\text{sim}}} - \overline{Q_{\text{obs}}}}{\overline{Q_{\text{obs}}}}, \quad (9)$$

where $\overline{Q_{\text{sim}}}$ and $\overline{Q_{\text{obs}}}$ denote the mean simulated and observed discharge over the evaluation period, respectively. The volumetric efficiency is defined as

$$\text{VE} = 1 - \frac{\sum_{t=1}^N |Q_{\text{obs},t} - Q_{\text{sim},t}|}{\sum_{t=1}^N |Q_{\text{obs},t}|}, \quad (10)$$

where $Q_{\text{obs},t}$ and $Q_{\text{sim},t}$ denote the observed and simulated discharge at time step t , respectively, and N is the number of
355 observations in the evaluation period. Whereas rBias quantifies the average signed error, VE measures the fraction of the observed discharge volume reproduced by the model under the assumption of an unbiased simulation (Criss and Winston, 2008). Because VE is based on absolute errors, it does not allow positive and negative deviations to cancel each other out, making it complementary to rBias. All metrics were computed separately for each spring and each model-catchment combination.

To further investigate whether the effect of catchment representation on model performance depends on the seasonality of
360 spring discharge, springs were clustered using the Pardé coefficient, a dimensionless indicator of intra-annual flow distribution commonly used in surface hydrology and previously applied to springs by Seelig et al. (2024a). The monthly Pardé coefficient is defined as

$$P_i = \frac{\overline{Q_i}}{\overline{Q_a}}, \quad (11)$$

where $\overline{Q_i}$ is the long-term mean discharge of month i and $\overline{Q_a}$ the long-term mean annual discharge, both expressed in L s^{-1} .
365 Pardé coefficients were computed using the complete discharge record (training and testing data), restricted to hydrological years with more than 80 % data availability to ensure robust estimates. The resulting monthly coefficient vectors were clustered using hierarchical agglomerative clustering with Ward's linkage criterion (Murtagh and Legendre, 2014), implemented in the scikit-learn library (Pedregosa et al., 2011). The number of clusters was set to four based on visual inspection of the dendrogram, yielding four distinct discharge regime types.

370 4 Validation Part I: Catchment approximation – results and discussion

Detailed results for Validation Part I are provided in Table D1, including all investigated springs and evaluation metrics. Maps comparing the reference and approximated catchments for each spring are provided in the Supplementary Materials (Sect. S1).

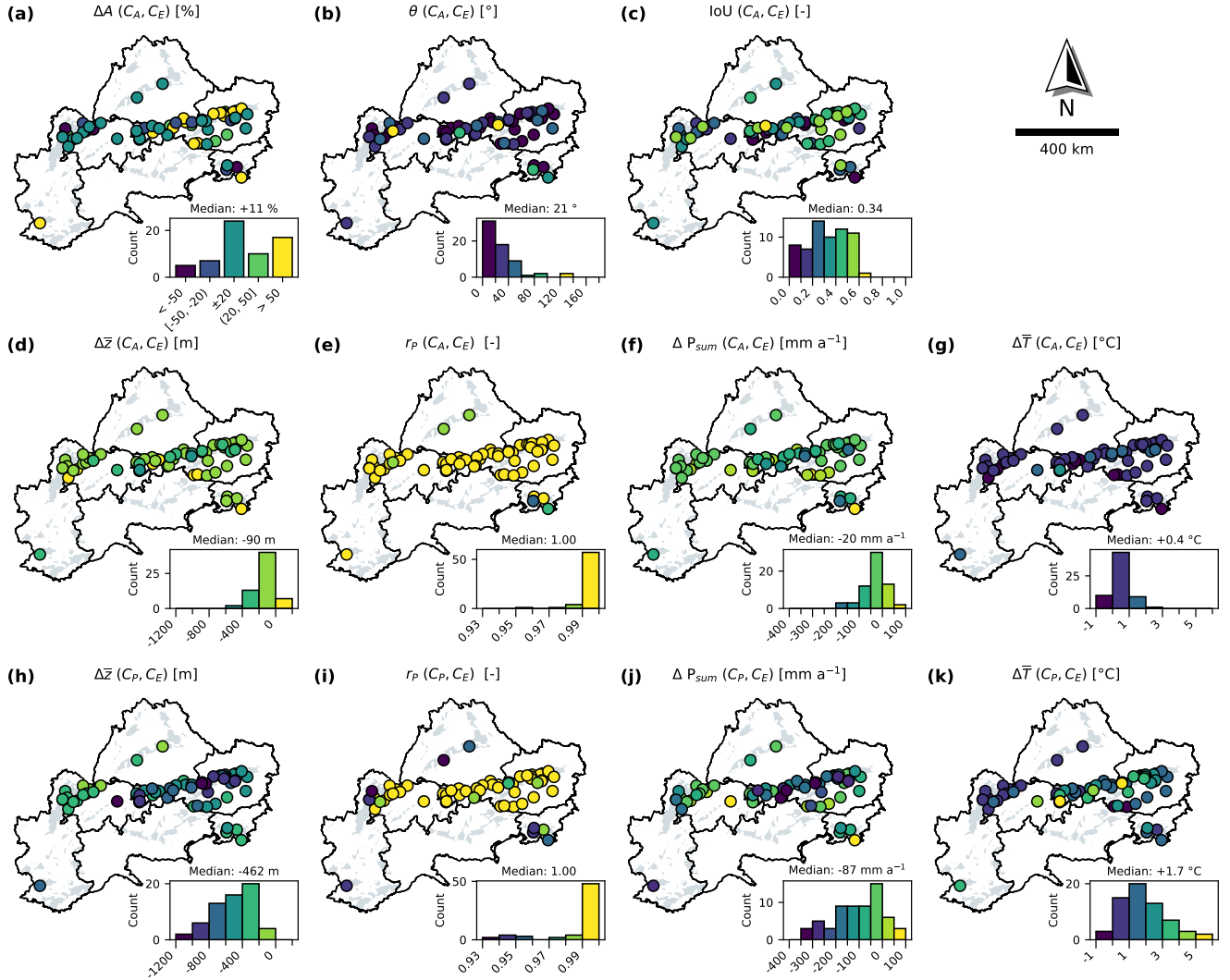


Figure 3. Spatial distribution of validation metrics for the approximated catchments (C_A) and the point-based representation (C_P) against the expert-delineated catchments (C_E), with each panel showing a map of the respective metric per spring alongside an inset histogram of its distribution. Panels (a)–(c) show metrics specific to the C_A – C_E comparison: (a) percentage area bias (ΔA), (b) angular deviation (θ), and (c) intersection over union (IoU). Panels (d)/(h), (e)/(i), (f)/(j) and (g)/(k) show, respectively, the difference in mean elevation ($\Delta \bar{Z}$), the Pearson correlation of aggregated precipitation (r_{precip}), the absolute difference in mean annual precipitation sum (ΔP_{sum}) and the difference in mean temperature ($\Delta \bar{T}$), each computed once for C_A vs. C_E (d–g) and once for C_P vs. C_E (h–k). Karst areas shown in grey are taken from MEDKAM (Xanke et al., 2024).



4.1 Recharge-area estimation

375 4.1.1 Convergence of the iterative estimation

For all but two springs, the estimated recharge area changed by less than the 5 % convergence threshold after two iterations (Fig. D2a). This rapid convergence can largely be attributed to the spatial resolution of ERA5-Land: for 54 of the 63 springs, the initial recharge-area estimate is smaller than a single ERA5-Land grid cell ($0.1^\circ \approx 85 \text{ km}^2$). Because most approximated catchments overlap only a few neighbouring grid cells, spatially aggregated recharge generally differs only marginally from
 380 the single-cell recharge used for the initial estimate. Consequently, the estimated recharge area stabilises rapidly. Only the Source de la Sorgue (FR-0024) and the Milandre karst system (CH-0026) required three and four iterations, respectively. For CH-0026, the iterative procedure was terminated because the estimated recharge area oscillated between two values, whereas FR-0024 exhibited clear convergence towards a stable recharge area (Fig. D2b). For FR-0024, the estimated recharge area decreased substantially from 7790 km^2 after the initial iteration to 2801 km^2 after convergence, illustrating the importance of
 385 the iterative procedure for large catchments with pronounced spatial heterogeneity in recharge, as is the case for the Source de la Sorgue (Ollivier et al., 2020).

4.1.2 Agreement in recharge-area size

Compared with the expert-based delineations, the water-balance-based approach shows a slight tendency to overestimate recharge area, with a median relative deviation of 11 %. Overall, 65 % of the springs show deviations within $\pm 50\%$, including 24 springs with deviations within $\pm 20\%$ (Fig. 3a). The 24 springs with deviations within $\pm 20\%$ include several
 390 well-investigated catchments: Ljubljana (SI-0016), Blautopf (DE-0015), Schlichenden Brünnen (CH-0005), and Source de l'Areuse (CH-0004). Substantial underestimations are observed in five cases, reaching up to 80 % for the Poltarica spring (SI-0042) and 72 % for the Source de la Birse (CH-0001). Strong overestimations are more frequent, exceeding 50 % in 17 springs and reaching a maximum of 530 %. These pronounced overestimations are concentrated in the inner Alpine region,
 395 particularly within the Northern Calcareous Alps of Austria. Potential causes of the observed over- and underestimations, including recharge uncertainty, karst-structural effects, and uncertainty in the expert-based reference catchments, are discussed in Sect. 6.1.

4.2 Catchment orientation and geometric agreement

The median angular deviation θ between the spring-to-centroid directions of C_E and C_A is 21° (Fig. 3b). Very good alignment
 400 ($\theta \leq 5^\circ$) is achieved for 14 springs (e.g. AT-0011: Dachserfall, Fig. 4a), whereas θ exceeds 90° in four cases: Unica (SI-0035), Alftzquelle (AT-0053), Schreiende Brunnen (AT-0014), and Source de la Birse (CH-0001, Fig. 4c). No distinct spatial pattern is apparent in the distribution of better- or worse-oriented catchments. The large angular deviations observed for individual springs indicate that surface topography does not always provide a suitable proxy for karst groundwater-flow direction. This is expected where subsurface drainage crosses topographic divides or is otherwise decoupled from the surface drainage network,

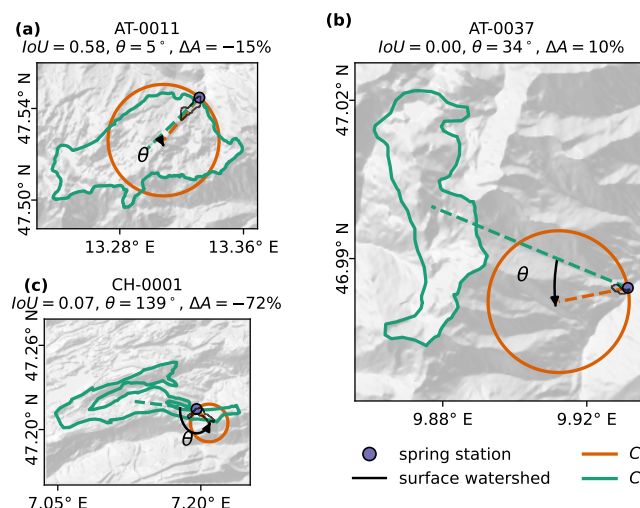


Figure 4. Comparison of the approximated catchment C_A , the expert-based catchment C_E , and the topographic catchment for (a) Dachserfall (AT-0011), (b) Fidelisque (AT-0037), and (c) Source de la Birse (CH-0001), including the angular deviation θ between the orientations of C_A and C_E relative to the spring. The hillshade is derived from the Copernicus DEM GLO-30 (ESA, 2022).

as illustrated by Source de la Birse (CH-0001), whose karst catchment extends beyond the surface watershed (Schindler, 1977). Nevertheless, the median angular deviation of 21° indicates that the topography-based approach can provide a reasonable first-order approximation of catchment orientation, despite substantial errors in individual cases.

The IoU ranges from 0 to 0.67, with a median of 0.34 (Fig. 3c). The highest IoUs are obtained for the Lehnbach springs (AT-0018: 0.67), Dachserfall (AT-0011: 0.58, Fig. 4a) and Pöllauer Ursprung (AT-0062: 0.57), while an IoU of 0—indicating no spatial overlap between the approximated and expert-based catchments—occurs for the Obwald, Fidelis, and Schreiende Brunnen springs (AT-0060, AT-0037 shown in Fig. 4b, and AT-0014). These cases differ markedly in their other metrics: AT-0014 also shows poor orientation ($\theta = 120^\circ$), whereas AT-0060 and AT-0037 show considerably smaller angular deviations ($\theta = 18^\circ$ and 34° , respectively) and area biases of 50 % and 10 %.

Across all springs, the percentage area bias ΔA shows no significant linear correlation with IoU (Fig. 5a). A large angular deviation θ is typically associated with low IoU, but the reverse does not hold: small angular deviations may still correspond to low IoU values—as exemplified by AT-0060 and AT-0037—so angular alignment alone is not a reliable predictor of spatial overlap (Fig. 5b). In contrast, IoU correlates significantly and positively with catchment circularity ($4\pi A/P^2$, where A and P denote the area and perimeter of the expert-based catchment delineation, respectively): lower circularity is associated with lower geometric agreement (Fig. 5c).

Overall, geometric agreement cannot be explained by recharge-area size or orientation alone. The relationship between circularity and IoU indicates that the imposed circular geometry itself constrains the achievable spatial agreement, particularly for elongated catchments. The approximation should therefore be interpreted as a simplified representation of catchment location,

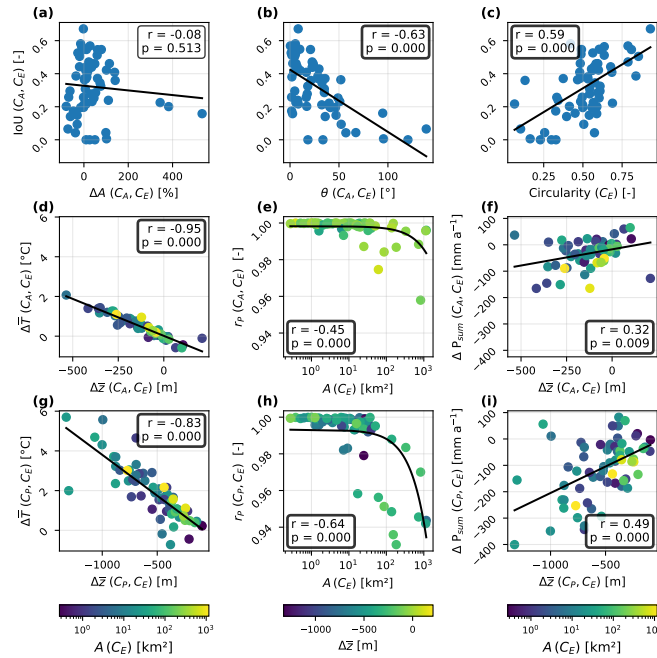


Figure 5. Relationships between geometric and hydro-meteorological validation metrics, shown as scatter plots with linear regression (black line), Pearson correlation coefficient, and p -value. Panels (a)–(c) relate to the geometric agreement between C_A and C_E : (a) intersection over union (IoU) vs. percentage area bias (ΔA), (b) IoU vs. angular deviation (θ), and (c) IoU vs. circularity of C_E . Panels (d)–(f) show relationships for the C_A – C_E comparison: (d) difference in mean temperature ($\Delta \bar{T}$) vs. difference in elevation ($\Delta \bar{z}$), coloured by the area of C_E ; (e) precipitation correlation (r_{prec}) vs. area of C_E , coloured by $\Delta \bar{z}$; and (f) difference in mean annual precipitation sum (ΔP_{sum}) vs. $\Delta \bar{z}$, coloured by the area of C_E . Panels (g)–(i) mirror (d)–(f), respectively, but for the C_P – C_E comparison.

extent, and orientation rather than as a reconstruction of the actual catchment boundary. Limitations of the topography-based orientation and circular approximation are discussed further in Sect. 6.2.

4.3 Representation of hydro-meteorological and topographic model inputs

4.3.1 Catchment elevation

For the approximated catchments C_A , mean elevation is underestimated relative to C_E by a median of 90 m (Fig. 3d), while in eight cases it is overestimated by up to 210 m. Deviations in mean elevation are particularly pronounced for springs in the inner Alpine region, where steep topographic gradients produce large elevation differences over short distances. In such high-relief settings, errors in catchment size, orientation, and shape can translate into substantial deviations in mean elevation. The strongest overestimation occurs for Alftuzquelle (AT-0053) and coincides with both a large angular deviation ($\theta = 96^\circ$) and a pronounced overestimation of catchment area ($\Delta A = +102\%$). Conversely, the strongest underestimation occurs for Fidelis spring (AT-0037; -536 m), for which C_A and C_E do not overlap ($\text{IoU} = 0$).



The point-based representation C_P shows a considerably stronger underestimation of mean elevation, with a median bias of
 435 -364 m (Fig. 3h). The underestimation reaches -1196 m for AT-0011 (Dachserfall). This systematic negative bias is expected,
 as C_P assumes a uniform elevation equal to the spring location and therefore neglects the elevation distribution within the
 recharge area. Because the recharge area is situated above the spring elevation (Goldscheider, 2010), the discrepancy becomes
 particularly pronounced where catchments extend over large elevation gradients.

4.3.2 Precipitation timing and annual totals

440 For dynamic input data, a generally high Pearson correlation is observed between precipitation aggregated over C_E , C_A , and
 C_P (Fig. 3e and i), indicating similar temporal patterns and timing of precipitation events. Correlations for C_P are generally
 lower (minimum 0.93 for DE-0015, Blautopf). The lowest correlations are mainly observed for larger catchments in Slovenia,
 Germany, and France, outside the inner Alpine region. Precipitation correlation r_P decreases with increasing catchment area
 $A(C_E)$ (Fig. 5e and h), particularly between C_E and C_P .

445 In contrast, no corresponding relationship is observed between precipitation correlation and differences in mean catchment
 elevation $\Delta\bar{z}$ (Fig. 5e and h), despite the generally greater spatial variability of precipitation in the Alps than in the European
 foreland (Hiebl and Frei, 2018). This may partly reflect the generally smaller size of the Alpine catchments in the dataset.
 Larger catchments encompass more grid cells, increasing the potential divergence between spatially aggregated precipitation
 (C_A , C_E) and the single-cell C_P representation. Potential effects of spatial smoothing in the gridded precipitation products are
 450 discussed in Sect. 6.4.1.

Annual precipitation sums are mostly lower for C_A and C_P than for C_E (Fig. 3f and j), with a median difference across
 all springs of -20 mm a $^{-1}$ for C_A and -87 mm a $^{-1}$ for C_P . The strongest underestimations occur in the Northern Calcareous
 Alps, reaching up to -165 mm a $^{-1}$ for C_A and nearly two and a half times that (-400 mm a $^{-1}$) for C_P . Annual precipitation-
 sum differences are significantly positively correlated with mean elevation differences, although the relationships are weak to
 455 moderate ($r_P = 0.32$ for C_A and $r_P = 0.49$ for C_P). In contrast to precipitation correlation, precipitation-sum differences show
 no consistent dependence on catchment size (scatter colour in Fig. 5f and i). The stronger deviations in annual precipitation
 sums observed in the inner Alpine region, and for larger differences in estimated mean catchment elevation, are consistent with
 orographic precipitation processes, whereby precipitation generally increases with elevation (Foresti and Pozdnoukhov, 2012).

4.3.3 Mean temperature

460 Differences in catchment elevation are also reflected in the temperature input. Deviations in mean temperature are stronger
 between C_P and C_E (median: $+1.7^\circ\text{C}$) than between C_A and C_E (median: $+0.4^\circ\text{C}$) (Fig. 3g and k). Consistent with the sys-
 tematic underestimation of mean elevation, mean temperature is predominantly overestimated, with $\Delta\bar{T}$ showing a significant
 negative relationship with $\Delta\bar{z}$ (Fig. 5d and g). The largest deviations again occur in the inner Alpine region. The temperature-
 elevation relationship derived from these data ($-0.37^\circ\text{C}(100\text{m})^{-1}$ for C_A and $-0.41^\circ\text{C}(100\text{m})^{-1}$ for C_P) is weaker than
 465 typical observed lapse rates in the Alps, typically varying between $-0.46^\circ\text{C}(100\text{m})^{-1}$ in winter and $-0.65^\circ\text{C}(100\text{m})^{-1}$ in



summer (Rubel et al., 2017). Potential effects of differences in the spatial resolution of the temperature and elevation datasets are discussed in Sect. 6.4.1.

Taken together, the automated catchment approximation provides a more representative description of hydro-meteorological model inputs than the point-based representation, particularly where spatial aggregation and topographic variability are important.

5 Validation Part II: Discharge modelling – results and discussion

5.1 Overall model performance

5.1.1 Performance across all springs

Performance metrics for all individual springs and model setups are provided in Table E1 for KarstMod and Tables E2 and E3 for the LSTM. For each spring, the Supplementary Materials (Sect. S1) provide hydrographs for the test period for all catchment representations and both model types, together with the corresponding performance metrics and maps comparing the catchment representations. For KarstMod, differences in performance across catchment representations are pronounced (Fig. 6b). The individually calibrated $KM-C_E$ and $KM-C_A$ models reach the same median KGE of 0.72, whereas $KM-C_P$ has a lower median KGE of 0.63 and is the only model setup with a distribution distinctly shifted towards lower values. Most low-KGE outliers, however, occur among the $KM-C_E$ models, showing that the use of the reference catchment does not necessarily result in better model performance for individual springs. The causes of these low-performing cases are examined further in Sect. 5.2.1.

For the global LSTM, the same tendency towards poorer performance with C_P is apparent, although differences between catchment representations are smaller, with median KGE ranging from 0.72 to 0.76 (Fig. 6c). All distributions are similarly skewed towards high KGE, with density concentrated near the upper end. Models using C_P for both static and dynamic inputs perform slightly worse than those using C_A or C_E . Notably, LSTMs using random static features achieve a slightly higher median KGE than those using environmental static features. The role of static features is examined further in Sect. 5.3.2.

Taken together, these results indicate that the effect of catchment representation depends strongly on model structure. KarstMod shows a clear overall performance penalty when the catchment is reduced to the point-based representation C_P , whereas C_A recovers the median performance obtained with C_E . In contrast, the global LSTM is less sensitive to the choice of catchment representation. The mechanisms underlying these contrasting responses are examined separately for KarstMod and the global LSTM in Sects. 5.2 and 5.3, respectively.

5.1.2 Dependence on discharge seasonality

The Pardé-based clustering identified four distinct discharge-seasonality regimes (Fig. 6a). Fourteen springs showed a nival-pluvial regime, characterised by low winter flow, a clear spring peak, and a second, less distinct peak in late summer to autumn; most of these springs are located in eastern Austria. Seventeen springs were classified as nival, also exhibiting low winter flow

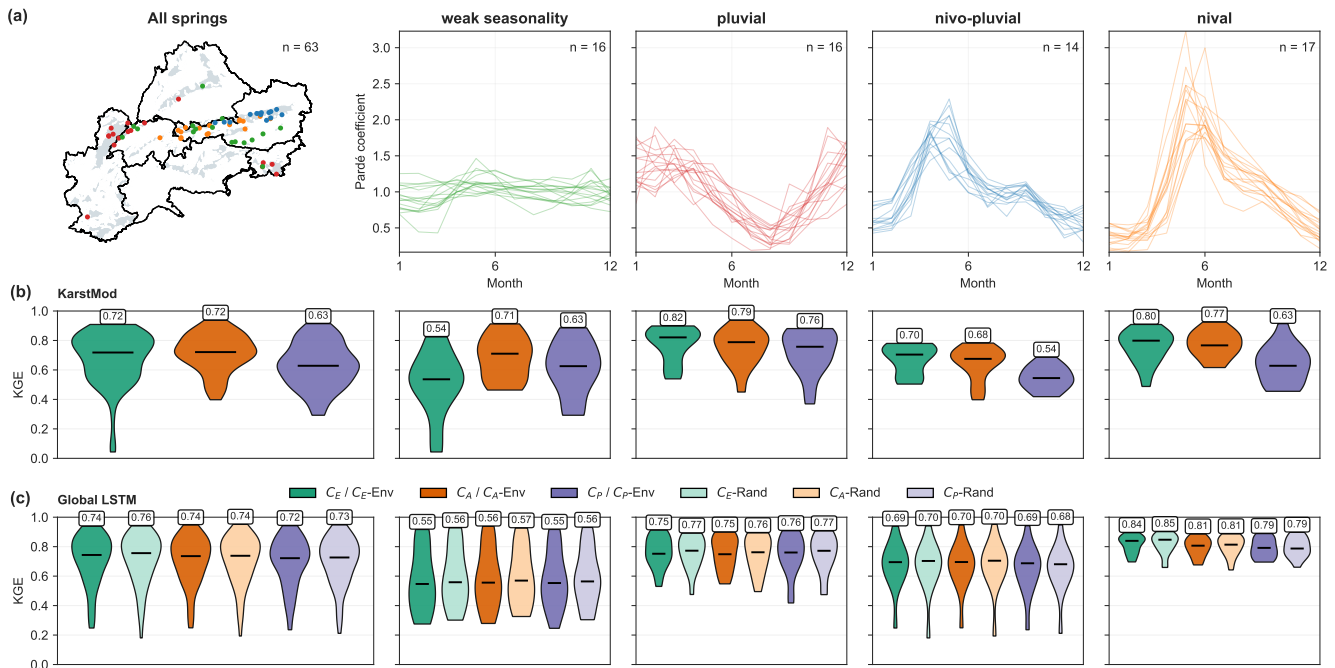


Figure 6. Overview of the identified spring discharge seasonality clusters. Each column represents one seasonality cluster, while the first column summarizes all 63 springs. (a) The map shows the spatial distribution of all 63 springs, coloured by seasonality cluster. The remaining columns show the individual Pardé curves of the springs belonging to each seasonality cluster. (b) Distribution of KGE for the reservoir model KarstMod across all springs and within each seasonality cluster, grouped by catchment representation. (c) Distribution of KGE for the global LSTM across all springs and within each seasonality cluster, grouped by catchment representation and static feature type.

but a more pronounced spring or early-summer peak than the nivo-pluvial group; these springs are concentrated in Switzerland and Austria. A pluvial cluster of 16 springs showed a clear dip in the Pardé curve in late summer and higher discharge in winter and spring, with springs located mostly in the French and Swiss Jura, the Dinarides, and the Swabian Alb. A fourth, weak-seasonality cluster of 16 springs showed no distinct seasonal pattern and did not fit any of the other three regimes; these springs are distributed across the entire study area, with a concentration in southern Austria.

For KarstMod, the influence of catchment representation differed markedly between seasonality clusters (Fig. 6b). For the weak-seasonality cluster, $KM-C_E$ performed worse than $KM-C_A$ and $KM-C_P$, with half of the springs showing a KGE below 0.54. In contrast, for the pluvial cluster, $KM-C_E$ performed best, with its distribution concentrated around $KGE = 0.82$. $KM-C_A$ showed a wider spread and slightly lower overall performance, with individual springs performing both better and worse than the range observed for $KM-C_E$. $KM-C_P$ showed fewer high-performing models and a longer lower tail, resulting in the lowest median KGE among the three representations. A similar but more pronounced pattern emerged for the nivo-pluvial and nival clusters, where $KM-C_A$ and $KM-C_E$ yielded comparable results—with some low-KGE outliers for $KM-C_A$ in the nivo-pluvial cluster—whereas $KM-C_P$ performed substantially worse.



510 The effect of catchment representation on KarstMod performance therefore depends on discharge seasonality. In particular, the performance penalty associated with C_P becomes most apparent for the nival and nivo-pluvial regimes, whereas no consistent advantage of a particular catchment representation is apparent for the weak-seasonality cluster. The stronger sensitivity of the snow-influenced regimes suggests a link to the representation of snow accumulation and melt. The roles of elevation, temperature, and snow processes in this pattern are examined in Sect. 5.2.3.

515 For the global LSTM, differences in KGE between catchment representations remain small within each seasonality cluster (Fig. 9c). The slight advantage of random over environmental static features observed across all springs is also present in each of the four clusters, indicating that this result is not driven by a single seasonality regime. A clear ranking among catchment representations emerges only for the nival cluster, where median KGE decreases from LSTM- C_E (Env: 0.84, Rand: 0.85) to LSTM- C_A (Env and Rand: 0.81) and LSTM- C_P (Env and Rand: 0.79), although this ranking is less pronounced for rBias, r ,
 520 and NSE (Table E2 and E3). Differences in performance between seasonality clusters are more pronounced than those between catchment representations: irrespective of catchment representation and static feature type, all global LSTM variants perform worst for the weak-seasonality cluster. One possible explanation is that these springs exhibit discharge dynamics that differ from the majority of the training set: 47 of the 63 springs belong to regimes with pronounced seasonality, whereas only 16 show weak seasonality. A similar sensitivity of global models to heterogeneous temporal dynamics was reported by Ohmer
 525 and Liesch (2026) for groundwater-level modelling, where excluding wells with dissimilar dynamics improved performance for the remaining wells. The lower performance of the weak-seasonality cluster may therefore reflect difficulties of the global LSTM in learning discharge dynamics that differ from those dominating the training dataset.

Compared with KarstMod, the global LSTM is therefore considerably less sensitive to catchment representation across discharge regimes.

530 5.2 KarstMod

The seasonality-based analysis showed that the response of KarstMod to catchment representation varies among discharge regimes. The following analysis examines these performance differences at the level of individual springs by relating them to the catchment-representation metrics derived in Validation Part I and to the corresponding calibrated model configurations. The analysis first considers controls on the simulated water balance and discharge bias, before examining their contribution to
 535 overall model performance and the specific role of elevation and temperature in snow-influenced catchments.

5.2.1 Controls on water balance and discharge bias

The rBias quantifies the relative difference between simulated and observed mean discharge, with negative values indicating underestimation and positive values indicating overestimation. Differences in rBias between catchment representations therefore reflect differences in the simulated discharge volume produced by the respective KarstMod variants. In KarstMod, the simulated
 540 water balance is jointly influenced by the prescribed recharge area, meteorological forcing, and calibrated model configuration and parameters, particularly those controlling evapotranspiration and discharge losses. Their individual contributions cannot

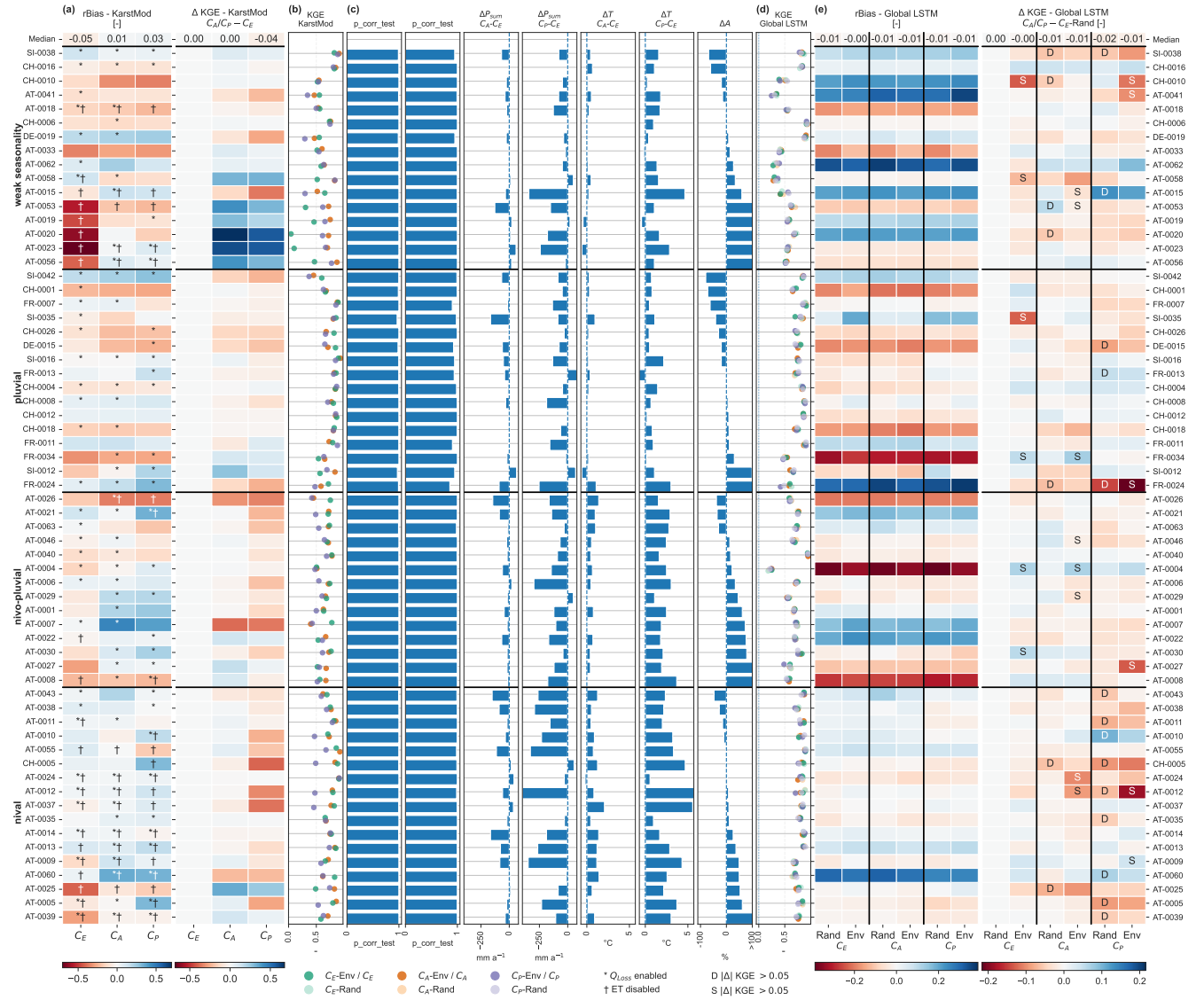


Figure 7. Impact of catchment representation on KarstMod and global LSTM performance, with springs grouped by seasonality cluster. Rows represent individual springs. (a,e) Heatmaps of $rBias$ (left) and ΔKGE (right) for KarstMod (a) and the global LSTM (e). For KarstMod, daggers indicate configurations without evapotranspiration (ET) and asterisks configurations including discharge loss (Q_{loss}). For the LSTM, ΔKGE is relative to LSTM- C_E -Rand; D and S mark differences > 0.05 associated with dynamic and static inputs, respectively. (b,d) KGE for all KarstMod (b) and global LSTM (d) configurations. (c) Validation-I metrics for C_A and C_P relative to C_E : precipitation correlation (r_P), annual precipitation difference (ΔP_{sum}), mean temperature difference (ΔT), and relative recharge-area difference (ΔA). ΔA is shown only for C_A because C_P retains the area of C_A .

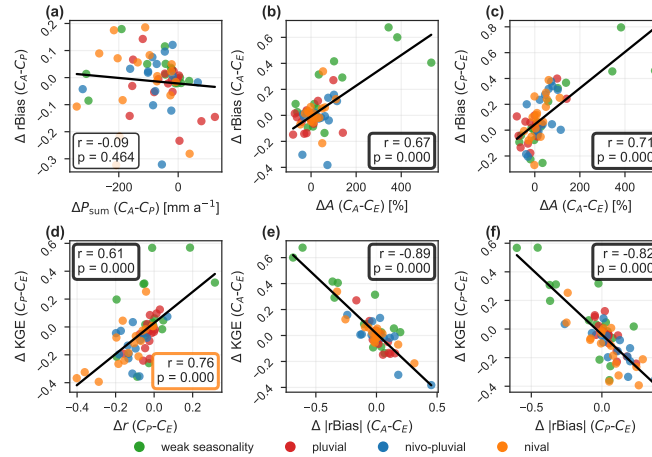


Figure 8. Relationships between catchment representation and KarstMod performance. Scatter plots show linear regressions with Pearson correlation coefficients (r) and p -values; boxes containing r and p are outlined in bold where $p < 0.05$. The upper row examines controls on discharge bias: (a) difference in rBias between KM- C_A and KM- C_P versus the corresponding difference in mean annual precipitation (ΔP_{sum}); both representations use the same recharge area. (b,c) Difference in rBias relative to KM- C_E versus the relative recharge-area difference (ΔA) for KM- C_A (b) and KM- C_P (c). The lower row examines controls on overall model performance: (d) difference in KGE between KM- C_P and KM- C_E versus the corresponding difference in timing error (Δr), and (e,f) difference in KGE versus the difference in rBias relative to KM- C_E for KM- C_A (e) and KM- C_P (f). Colours distinguish discharge-seasonality clusters.

be fully separated because changing the catchment representation alters several of these components simultaneously. However, comparison of the model bias for the three catchment representations allows their relative influence to be partially constrained.

Because KM- C_A and KM- C_P use the same prescribed recharge area, differences in rBias between them cannot be attributed to recharge-area size. Differences in annual precipitation sum between C_A and C_P show no significant linear relationship with the corresponding differences in rBias (Fig. 8a), indicating that differences in annual precipitation totals alone do not explain the observed changes in simulated discharge volume. This is evident, for example, for AT-0015 (Stubbachquelle), where annual precipitation differs by 310 mm a^{-1} while rBias differs by only 0.01, and for SI-0012 (Bilpa), where a precipitation difference of only 4 mm a^{-1} coincides with a high rBias difference of 0.23. These contrasting cases indicate that the response to meteorological forcing is modified and compensated by model parameters.

When comparing KM- C_E with KM- C_A and KM- C_P , recharge area, meteorological forcing, and calibrated model parameters vary simultaneously, preventing the contribution of any single component from being isolated. Nevertheless, differences in rBias are significantly and positively correlated with ΔA for both the KM- C_A –KM- C_E and KM- C_P –KM- C_E comparisons (Fig. 8b,c). Thus, a larger prescribed recharge area is generally associated with a more positive rBias, consistent with an increase in simulated mean discharge.

This relationship is particularly apparent for springs with strongly positive ΔA . Notably, for several springs in the weak-seasonality cluster with $\Delta A \gg 0$, KM- C_E exhibits pronounced discharge underestimation (e.g. AT-0023: Moosbrunnquelle,



rBias = -0.70), while the larger recharge area prescribed for KM- C_A and KM- C_P shifts rBias substantially closer to zero (Fig. 7a). Similar behaviour occurs in the other seasonality clusters, including SI-0012 (Bilpa, pluvial), AT-0027 (Große Mühlequelle, nivo-pluvial), and AT-0025 (Siebenbrunnenquelle, nival). Thus, the larger estimated recharge area can in some cases provide a water balance that is more consistent with the observed mean discharge than the expert-based area. Conversely, strongly negative ΔA is often associated with a more negative and less favourable rBias for KM- C_A and KM- C_P , as illustrated by AT-0026 (Lastal-Stollenquelle).

While a better agreement in rBias for C_A could be consistent with an underestimated reference catchment area and thus uncertainties in the reference catchment (Sect. 6.3), it does not necessarily imply that C_A provides a more accurate physical delineation of the recharge area. The observed pattern could also arise from uncertainty in meteorological forcing, particularly precipitation underestimation (Sect. 6.4.1). This is especially relevant because C_A is itself derived from a water balance using gridded meteorological data. If recharge per unit area is underestimated, the water-balance approach compensates by estimating a larger recharge area. Improved rBias with C_A may therefore indicate a more suitable effective recharge area for modelling rather than a more accurate physical catchment boundary.

The relationship between recharge-area difference and rBias is not universal, as indicated by the scatter around the relationships (Fig. 8b and c). For example, AT-0008 (Miesenbachursprung) shows only minor differences in rBias despite a large positive ΔA . Such deviations indicate that recharge-area size alone does not determine the simulated water balance and that other model components can modify or compensate for its effect. Potential for such compensation arises from both the selected model configuration and the calibrated parameters.

KarstMod is calibrated using eight predefined model configurations (Sect. 3.3.1), from which the best-performing configuration is selected. Two structural choices directly affect the water balance: evapotranspiration can be omitted, thereby retaining more water within the system, whereas activation of Q_{loss} introduces an additional loss flux. Further adjustment is possible through calibrated parameters controlling storage and emptying of the epikarst reservoir, both of which affect simulated actual evapotranspiration. In the rBias heatmap (Fig. 7a), configurations without evapotranspiration are indicated by †, whereas configurations including Q_{loss} are indicated by *.

Several individual springs illustrate how these degrees of freedom can compensate for differences in catchment representation. For AT-0008 (Miesenbachursprung), rBias differs only slightly among catchment representations despite a large ΔA . However, the selected configurations differ: KM- C_E omits evapotranspiration, KM- C_A includes Q_{loss} , and KM- C_P combines both modifications. Similarly, AT-0015 (Stubbachquelle) shows nearly identical rBias for KM- C_A and KM- C_P despite a large difference in annual precipitation input; Q_{loss} is activated for KM- C_A but not for KM- C_P . These examples are consistent with calibration partly compensating for differences in area and meteorological forcing: omission of evapotranspiration can increase the water available for discharge, whereas Q_{loss} can remove excess water from the simulated system. Similar compensation for systematic precipitation bias through adjustment of evapotranspiration-related processes has been reported for lumped hydrological modelling by Wang et al. (2023).

Such differences in calibrated configuration should not, however, be interpreted exclusively as compensation for input errors. In some cases, the selected structure is consistent with known hydrological behaviour. For Malenščica (SI-0035), for example,



Q_{loss} is selected for all three catchment representations and can plausibly represent transfer towards the Unica spring once the discharge capacity of Malenščica is exceeded (Ravbar and Kovačič, 2016). Configurations without evapotranspiration occur predominantly for Austrian springs and are most frequent in the nival cluster, whereas none are selected within the pluvial cluster. In some cases, this may reflect physically low evapotranspiration in high-elevation, sparsely vegetated, and strongly karstified catchments with rapid infiltration (Malard et al., 2016), such as the Fidelisque (AT-0037), whose catchment lies entirely above 1900 m a.s.l. and is characterised by strongly karstified limestone (Mathis, 2005). However, complete omission of evapotranspiration may also reflect calibration compensation for uncertainties in meteorological forcing or model structure (Sect. 6.4).

These findings suggest that differences in KarstMod rBias cannot be uniquely attributed to recharge-area size, meteorological forcing, or calibration response. Nevertheless, the significant relationship between ΔA and changes in rBias for both KM- C_A and KM- C_P indicates that the prescribed recharge area is an important control on the simulated water balance. Deviations from this relationship, together with the differences in selected model configurations, indicate that calibration can partly compensate for differences in recharge area and meteorological forcing, particularly through evapotranspiration and discharge-loss processes. These findings support interpreting the recharge area used by a lumped model as an effective hydrological parameter that does not necessarily correspond exactly to the physical recharge-area boundary (Jeannin et al., 2021).

5.2.2 Controls on overall model performance

While the preceding analysis focused on differences in the simulated water balance, KGE additionally accounts for correlation and variability (Gupta et al., 2009). Differences in absolute rBias are significantly correlated with differences in KGE for both the KM- C_A –KM- C_E and KM- C_P –KM- C_E comparisons (Fig. 8e,f). Thus, the catchment representation yielding rBias closer to zero generally also achieves the higher KGE. This relationship is particularly apparent for the weak-seasonality springs with large ΔA and strongly negative rBias for KM- C_E , as well as for SI-0012, AT-0027, and AT-0025. The strong discharge underestimations observed for these springs also account for several of the low-KGE outliers of KM- C_E identified in Sect. 5.1.1. Conversely, lower KGE for KM- C_A or KM- C_P is frequently associated with a less favourable rBias, as observed for SI-0042, CH-0026, DE-0015, FR-0024, and AT-0060, where mean discharge is substantially over- or underestimated. Differences in the simulated water balance therefore explain a substantial part of the variation in overall model performance between catchment representations.

However, the relationship between differences in absolute rBias and KGE is weaker for the KM- C_P –KM- C_E comparison than for KM- C_A –KM- C_E , indicating that water-balance differences alone do not explain the performance differences associated with the point-based representation. Differences in the Pearson correlation coefficient r , which reflects agreement in the temporal dynamics of simulated and observed discharge, are also significantly associated with ΔKGE for KM- C_P . This relationship is strongest within the nival cluster ($r = 0.76$), indicating that differences in discharge dynamics contribute particularly strongly to the poorer overall performance of KM- C_P for snow-dominated springs. The influence of elevation and temperature representation on snow accumulation, melt timing, and discharge seasonality is examined in Sect. 5.2.3.



In contrast, no consistent relationship is apparent between precipitation correlation r_P and ΔKGE . Although several springs with comparatively low r_P also show reduced KGE (e.g. DE-0015, FR-0007, SI-0016, and FR-0024), these cases simultaneously exhibit less favourable rBias, preventing the performance differences from being attributed specifically to precipitation timing. Moreover, r_P remains high across all catchment representations (Sect. 4.3.2), indicating that both C_A and C_P generally
 630 preserve the temporal pattern of precipitation represented by C_E . Consequently, differences in precipitation timing as represented by the gridded datasets appear to contribute less to the observed differences in KarstMod performance than differences in the water balance and, particularly for KM- C_P in nival catchments, discharge dynamics.

No consistent relationship is observed between IoU and differences in KGE. Even for AT-0014 (Schreiende Brunnen), where C_A and C_E do not overlap ($IoU = 0$), KM- C_A achieves a KGE close to that of KM- C_E ($\Delta KGE = -0.02$), indicating that
 635 close geometric agreement is not a prerequisite for similar model performance.

5.2.3 Effects of elevation and temperature on snow seasonality

To investigate the hydrological origin of the poorer KM- C_P performance in snow-influenced catchments, modelled discharge seasonality is examined using Pardé curves together with differences in mean catchment temperature ($\Delta \bar{T}$) and elevation ($\Delta \bar{z}$) derived in Validation Part I (Sect. 4.3). Pronounced differences among KM- C_E , KM- C_A , and KM- C_P emerge for the nival
 640 and nivo-pluvial clusters, whereas modelled seasonality remains largely unaffected by catchment representation for the pluvial and weak-seasonality clusters. Per-spring Pardé curves for the latter three clusters are provided in the Supplementary Materials (Sect. S2).

Within the nival cluster, increasing $\Delta \bar{T}(C_P - C_E)$ is associated with an increasingly poor representation of discharge seasonality by KM- C_P (Fig. 9). For springs with large positive temperature differences, KM- C_P produces a substantially less
 645 nival discharge regime, characterised by overestimated winter discharge and underestimated discharge during the snowmelt period, as illustrated by CH-0005 (Schlichenden Brünnen) and AT-0012 (Schwarze Torrenquelle). KM- C_A generally reproduces seasonality more closely than KM- C_P , but deviations from KM- C_E remain where the approximated catchment poorly represents the elevation distribution. For example, the elevation distribution of C_A for AT-0043 (Wassermannsloch) is shifted towards lower elevations relative to C_E , accompanied by differences in modelled seasonality. Conversely, where temperature
 650 differences between catchment representations are small, the effect on seasonality is limited. For AT-0024 (Ursprungquelle), for example, $\Delta \bar{T}(C_P - C_E) = +0.6^\circ\text{C}$ and $\Delta \bar{T}(C_A - C_E) = -0.2^\circ\text{C}$, and the Pardé curves of all three model-catchment combinations are closely aligned.

The response of the calibrated snow parameters provides evidence that KarstMod can partly compensate for these temperature differences. Snowmelt timing and magnitude are controlled by the calibrated threshold temperature T_{thr} (-1 to 1°C) and
 655 melt factor MF (0.5 to $6\text{mm}^\circ\text{C}^{-1}\text{d}^{-1}$), respectively (Table 1). Across the nival and nivo-pluvial springs, MF tends to be lower for KM- C_A and KM- C_P than for KM- C_E , whereas T_{thr} tends to be higher (Fig. E1). Differences in both parameters are generally smaller where $\Delta \bar{T}$ is close to zero. A higher T_{thr} delays the onset of snowmelt, while a lower MF reduces the melt rate. Together, these parameter adjustments can partly compensate for the warmer temperature input resulting from underestimated catchment elevation by mimicking snowmelt conditions associated with a higher-elevation catchment. Similar

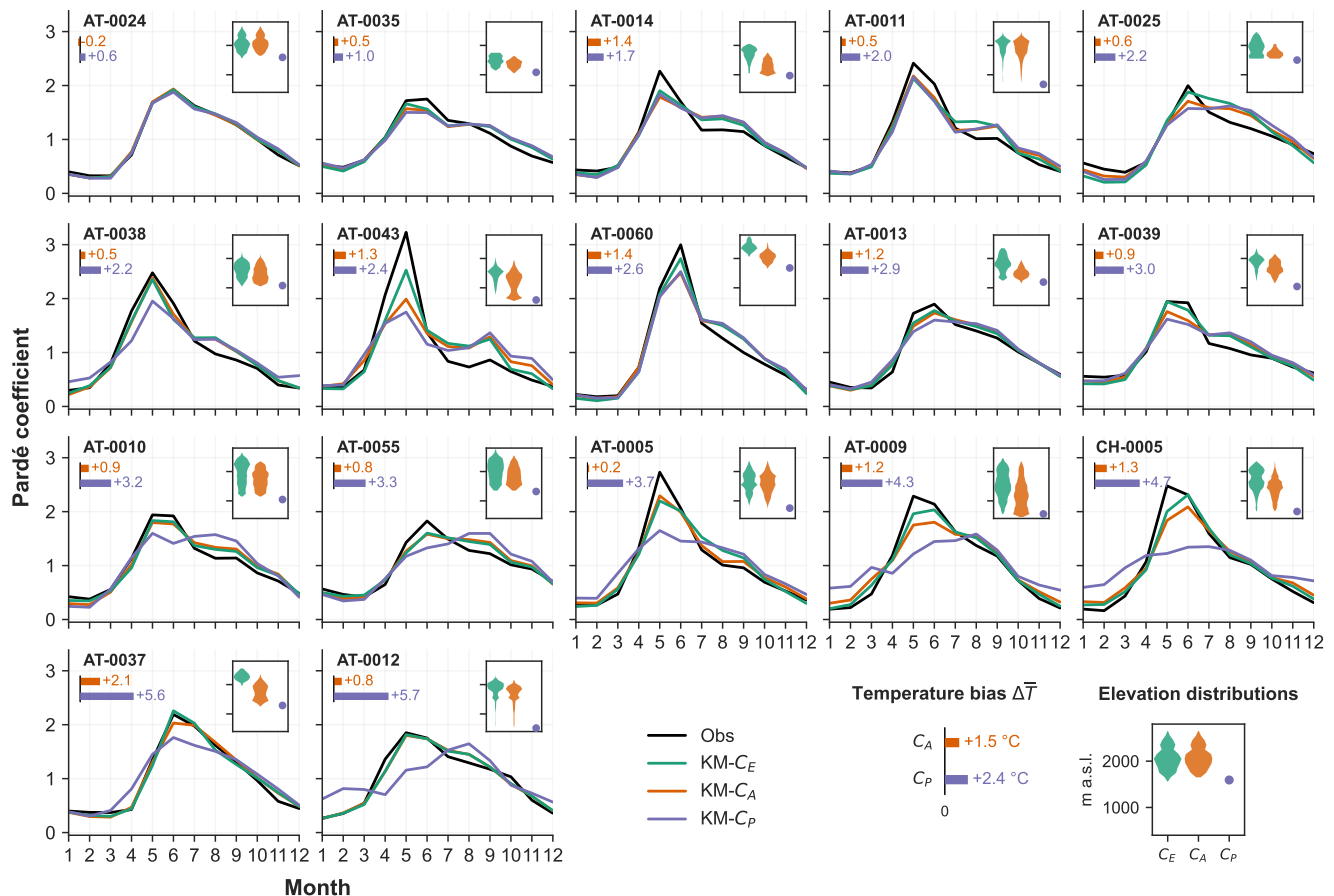


Figure 9. Observed and KarstMod-modelled spring discharge seasonality, shown as Pardé curves for each spring individually for the nival cluster. Each subplot shows four curves (observed, C_E , C_A , C_P), together with inset plots showing the elevation distributions of the three catchment representations and the mean temperature differences $\Delta\bar{T}$ for C_A and C_P relative to C_E . Curves are based on hydrological years with data availability > 80 %. Subplots are arranged in a grid, ordered left to right and top to bottom by increasing $\Delta\bar{T}(C_P - C_E)$.

660 compensation of uncertain forcing through calibrated parameters in degree-day snow routines has been demonstrated by Clark and Vrugt (2006), who also showed that such compensation can result in parameter values that do not retain a direct physical interpretation. Notably, T_{thr} is consistently calibrated above 0°C across all catchment representations, indicating a systematic tendency to delay simulated snowmelt relative to the temperature forcing. This may reflect compensation for forcing or model-structural uncertainty independent of catchment representation, as discussed in Sect. 6.4.2.

665 The effectiveness of parameter compensation decreases as the temperature discrepancy between catchment representations increases. Where $\Delta\bar{T}$ remains within approximately $\pm 1^\circ\text{C}$, modelled seasonality is generally similar among catchment representations, indicating that the available parameter flexibility can compensate for moderate temperature differences. In contrast, temperature differences exceeding approximately 2°C are associated with pronounced deterioration of the KM- C_P seasonality,

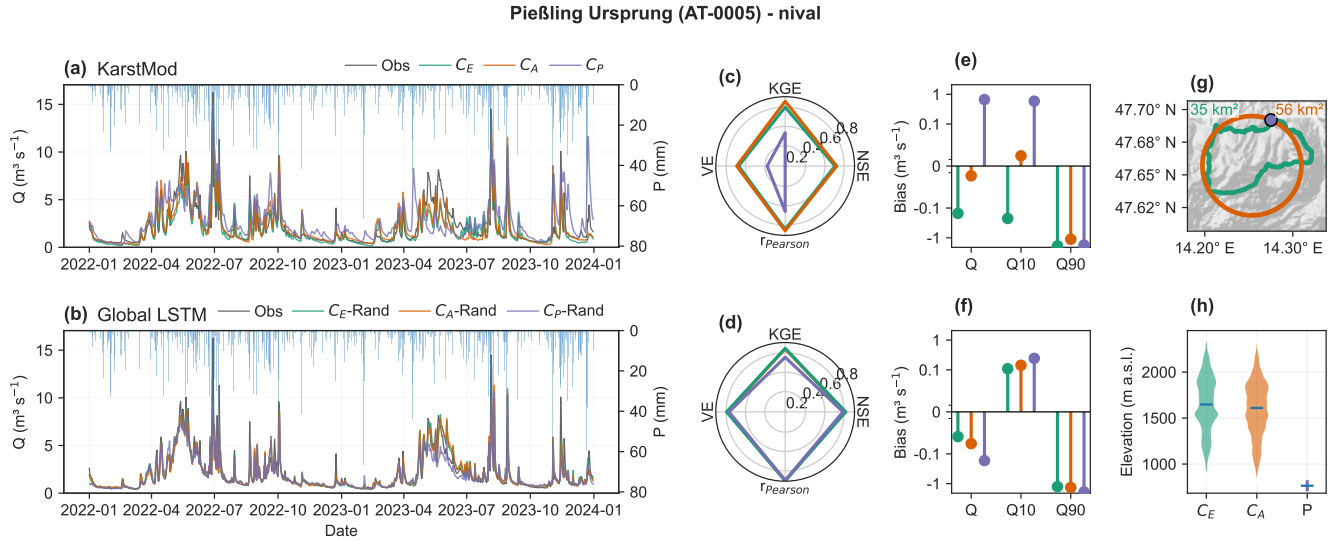


Figure 10. Detailed model performance for spring AT-0005. The first panel of each pair shows KarstMod and the second the global LSTM. (a, b) Hydrographs of observed and simulated discharge during the test period for the different catchment representations. (c, d) Spider plots of KGE, NSE, Pearson correlation (r), and volumetric efficiency (VE). (e, f) Bias for low flow (Q_{10} , 10th percentile), high flow (Q_{90} , 90th percentile), and overall flow (Q), shown on a logarithmic y-axis. (g) Map showing the delineated catchment boundaries for all three catchment representations (C_E , C_A , C_P), with hillshade derived from the Copernicus DEM GLO-30 (ESA, 2022). The expert-based catchment delineation (C_E) is taken from the ALPAKAS dataset (Joger et al., 2026b). (h) Elevation distributions of C_E , C_A , and C_P , shown as violin plots.

including premature winter discharge and insufficient discharge during the subsequent melt period. The prescribed calibration
 670 range of T_{thr} therefore appears insufficient to compensate fully for large temperature discrepancies. Because temperature bi-
 ases are generally smaller for C_A than for C_P , the snow routine can more frequently compensate for errors introduced by the
 approximated catchment representation.

Pießling Ursprung (AT-0005) illustrates the effect of catchment elevation on snow-dominated discharge seasonality particu-
 larly clearly (Fig. 10). While C_A reproduces the mean elevation of C_E within 52 m, C_P underestimates it by 843 m (Fig. 10h).
 675 This difference is reflected in the calibrated snow parameters: KM- C_A remains close to KM- C_E ($MF = 2.0$ vs. 2.1 mm a^{-1} ;
 $T_{thr} = 0.74$ vs. 0.82°C), whereas KM- C_P calibrates a substantially lower MF (0.6 mm a^{-1}) and higher T_{thr} (0.91°C), con-
 sistent with the compensation mechanism described above. Despite this adjustment, KM- C_P reproduces the observed discharge
 seasonality substantially less well than KM- C_A and KM- C_E (Fig. 10a, c, e). It produces pronounced discharge peaks during
 winter precipitation events, when observed discharge remains low, and shows the largest underestimation during the 2023
 680 snowmelt period. Consequently, KM- C_P performs worse in KGE, NSE, and discharge correlation and strongly overestimates
 low flows. In contrast, KM- C_A closely approaches the performance and seasonal dynamics obtained with the expert-based



catchment. AT-0005 therefore provides a clear example of how the improved elevation representation of C_A can preserve snow-dominated discharge dynamics that are lost when meteorological forcing is extracted at the spring location.

Importantly, not all discrepancies in snow-dominated discharge seasonality can be attributed to catchment representation. For several springs, all three KarstMod model-catchment combinations, including $KM-C_E$, underestimate the late-spring snowmelt peak and overestimate autumn discharge (e.g. AT-0014: Schreiende Brunnen, AT-0011: Dachserfall, and AT-0043: Wassermannsloch; Fig. 9). These systematic deviations indicate additional limitations in the meteorological forcing or snow routine that are independent of catchment representation and are discussed in Sect. 6.4.

Nevertheless, the results show that the improved representation of catchment elevation by C_A reduces temperature biases and thereby better preserves snow-dominated discharge seasonality compared with C_P .

5.3 Global LSTM

5.3.1 Sensitivity to dynamic meteorological input

Differences between catchment representations are less pronounced for the global LSTM than for KarstMod, as already indicated by the narrower colour range of the heatmaps (Fig. 7e). All three representations show similar rBias behaviour, and, unlike for KarstMod, ordering springs by over- and underestimation of catchment area (ΔA) reveals no systematic pattern.

Since the random static input is identical for $LSTM-C_E$ -Rand, $LSTM-C_A$ -Rand, and $LSTM-C_P$ -Rand, performance differences between these models reflect differences in dynamic meteorological input. Using $LSTM-C_E$ -Rand as the reference, pronounced performance differences ($|\Delta KGE| > 0.05$) are indicated by a “D” in Fig. 7e.

Across the weak-seasonality and pluvial clusters, differences in dynamic input generally result in only small changes in LSTM performance. Median pairwise ΔKGE values relative to $LSTM-C_E$ -Rand range from -0.01 to 0.00 for $LSTM-C_A$ -Rand and from -0.02 to 0.00 for $LSTM-C_P$ -Rand. Although individual differences exceeding $|\Delta KGE| = 0.05$ occur, they do not consistently indicate poorer performance of the approximate representations. For example, $LSTM-C_P$ -Rand outperforms $LSTM-C_E$ -Rand by $\Delta KGE = +0.13$ for AT-0015 despite substantially lower annual precipitation and higher mean temperature. In the pluvial cluster, strong performance differences sometimes coincide with pronounced differences in precipitation correlation (e.g. FR-0024: Source de la Sorgue) and/or annual precipitation sums, but such meteorological differences do not systematically translate into lower KGE.

Thus, meteorological input derived from the reference catchment does not necessarily improve the global LSTM. In contrast to KarstMod, the LSTM is not constrained by water-balance principles but learns a direct mapping between meteorological forcing and discharge (Kratzert et al., 2018). Consequently, physically more representative catchment precipitation is not necessarily required to reproduce the observed discharge response. A similar robustness of LSTMs to input uncertainty compared to process-based models was reported by Kim et al. (2026), who suggested that information contained across sequential inputs may partly compensate for errors at individual time steps.

In contrast, sensitivity to catchment representation increases for snow-influenced springs. In the nivo-pluvial cluster, $LSTM-C_P$ -Rand performs slightly worse than $LSTM-C_E$ -Rand overall (median $\Delta KGE = -0.02$), whereas $LSTM-C_A$ -Rand shows



715 a marginal improvement (+0.01). LSTM- C_P -Rand performs worse than LSTM- C_E -Rand for 11 of 14 springs, compared with 6 of 14 for LSTM- C_A -Rand. These differences coincide with substantially larger deviations in mean temperature and annual precipitation for C_P than for C_A (Fig. 7c).

The pattern is stronger in the nival cluster, where $|\Delta\text{KGE}| > 0.05$ occurs for 9 of 17 springs for LSTM- C_P -Rand but only 2 of 17 for LSTM- C_A -Rand. In most affected springs, C_P substantially overestimates mean temperature and underestimates
720 annual precipitation relative to C_E . With two exceptions, the resulting KGE differences are negative. This systematic direction, together with the larger meteorological deviations for C_P , suggests that the LSTM becomes more sensitive to catchment representation where discharge seasonality strongly depends on temperature-controlled snow accumulation and melt, which the model must infer implicitly from precipitation and temperature.

AT-0005 illustrates this behaviour (Fig. 10b, d, f). LSTM- C_P -Rand shows a lower KGE than LSTM- C_E -Rand and LSTM-
725 C_A -Rand ($\Delta\text{KGE} = -0.08$ and 0.00 , respectively) and more strongly underestimates peak discharge, while peak timing remains similar among the three representations. The largest divergence occurs in June 2023, when LSTM- C_E -Rand and LSTM- C_A -Rand overestimate discharge whereas LSTM- C_P -Rand underestimates it. Similar behaviour occurs for several other nival and nivo-pluvial springs tested in 2023, whereas differences between catchment representations are considerably smaller during summer 2022. The particularly strong divergence during the exceptionally warm 2023 snowmelt season in Austria (GeoSphere
730 Austria, 2023) and Switzerland (MeteoSwiss, 2023) suggests that the influence of catchment representation may increase under meteorological conditions that are poorly represented in the training period, such as the warm summer of 2023. Under such conditions, differences in meteorological forcing between catchment representations may lead to increasingly divergent model responses.

Taken together, the global LSTM is considerably less sensitive to catchment representation than KarstMod. For weak-
735 seasonality and pluvial springs, spatially aggregated meteorological input provides little systematic advantage over single-cell forcing. In snow-influenced catchments, however, the naive point representation more frequently degrades performance, whereas the approximated catchment C_A produces meteorological input and discharge simulations closer to those obtained with the reference catchment C_E . The coincidence of these performance differences with larger temperature and precipitation deviations for C_P suggests that an adequate spatial representation of meteorological forcing becomes more relevant where
740 discharge dynamics are strongly influenced by snow accumulation and melt.

5.3.2 Role of environmental static features

Models using identical dynamic input but different static features—environmental or random (e.g. LSTM- C_E -Env versus LSTM- C_E -Rand)—allow the influence of static input to be assessed independently of meteorological forcing. Absolute KGE differences exceeding 0.05 are marked by an "S" in the corresponding heatmap cell (Fig. 7e), indicating pronounced performance deviations associated with differences in static features.
745

Overall, environmentally meaningful static features provide little systematic benefit over random static input. Strong differences ($|\Delta\text{KGE}| > 0.05$) between LSTM-Env and LSTM-Rand occur for six springs under C_E , eight under C_A , and six under C_P , but their direction is inconsistent: LSTM-Env performs better in three, two, and one of these cases, respectively. Consid-



ering all springs, environmental features outperform random features in fewer than half of the cases (27 of 63 for C_E , 30 for
 750 C_A , and 26 for C_P). Accordingly, the median pairwise KGE differences (Env minus Rand) are close to zero for all catchment
 representations (-0.005 , -0.004 , and -0.000 , respectively). Together with the similar or slightly higher median KGE of the
 random models within the seasonality clusters, these results indicate that environmental static features provide virtually no
 systematic in-sample performance advantage, regardless of whether they are derived from C_E , C_A , or C_P .

This result is consistent with previous studies showing that, in in-sample-testing (temporal testing on catchments included
 755 in training data), random unique identifiers can achieve similar performance to environmental static features (Li et al., 2022).
 They are further consistent with Heudorfer et al. (2024), who report that in hydrogeological applications static features tend to
 act as unique identifiers rather than enabling generalisation through the transfer of learned patterns to similar catchments, as
 suggested by Kratzert et al. (2019c) for hydrology applications. If the static features primarily serve this identification function,
 the slight advantage of the random models observed here may partly result from the greater distinctiveness of random feature
 760 combinations, whereas similar environmental characteristics can result in less distinguishable feature representations among
 springs.

Nevertheless, individual cases show that environmental static information can affect model performance substantially. Envi-
 ronmental features improve KGE by more than 0.05 for three springs under C_E and two under C_A , suggesting that informative
 static attributes may benefit individual springs. Conversely, they may also degrade performance when the encoded environ-
 765 mental similarity does not correspond to similarity in discharge dynamics. The clearest example is Unica (SI-0035), for which
 LSTM- C_E -Env performs substantially worse than LSTM- C_E -Rand ($\Delta\text{KGE} = -0.13$). Its reference catchment is nearly iden-
 tical to that of Malenščica (SI-0038), differing mainly in the Lower Pivka basin, which drains solely towards Unica (Ravbar
 and Kovačič, 2016). Consequently, the two springs receive very similar environmental static features despite differences in
 their hydrological behaviour: different parts of the catchment contribute to the two springs depending on hydrological condi-
 770 tions, while Malenščica exhibits lower discharge variability and a constrained maximum discharge (Ravbar and Kovačič, 2016;
 Ravbar et al., 2012). The static features may therefore encode a similarity between the two springs that is not fully reflected in
 their discharge dynamics, potentially explaining why environmental features degrade performance for SI-0035.

The environmental features used here may therefore not capture hydrologically relevant differences among springs suffi-
 ciently well to provide a systematic advantage over random identifiers. Their usefulness depends not only on the underlying
 775 catchment representation, but also on whether the selected attributes adequately describe the characteristics controlling differ-
 ences in spring discharge behaviour. This is consistent with Liesch and Ohmer (2026), who found that static features provide
 an advantage beyond acting as unique identifiers only when their information content is sufficient. In the present in-sample
 evaluation, however, there is no systematic indication that static features derived from the expert-based C_E provide an advan-
 tage over those derived from the approximate or point-based representations. Thus, unlike the dynamic meteorological input in
 780 snow-influenced catchments, differences in environmental static features do not reveal a clear performance benefit of improved
 catchment representation for the global LSTM.



6 Uncertainties and limitations

6.1 Uncertainties in recharge-area estimation

Uncertainty in the estimated recharge-area size arises from both the water-balance approach and karst-specific flow behaviour
785 that cannot be represented by a simplified, single-outlet water balance.

6.1.1 Input-data and methodological uncertainty

Recharge-area estimates depend directly on mean discharge and estimated recharge, and are therefore affected by the length and representativeness of the discharge records as well as by the accuracy and coarse spatial resolution of the ERA5-Land data. In particular, underestimated recharge results in overestimated recharge areas. This may explain the concentration of strong
790 overestimations in the Northern Calcareous Alps (Sect. 4.1.2), where infiltration rates can reach 90 % in high-elevation bare karst due to thin or absent soils and low evapotranspiration (Malard et al., 2016). Under these conditions, the presented approach may underestimate recharge, as accurately representing recharge in karst environments remains challenging (Zeitfogel et al., 2025; Wan et al., 2024).

The Source de la Sorgue (FR-0024) illustrates this uncertainty. Although iteration substantially reduces its initial area estimate (Sect. 4.1.1), the converged estimate remains 2.4 times the expert-based impluvium. For 1996–2011, our estimated mean
795 annual recharge of 158 mm is considerably lower than independent estimates of 335 to 412 mm for the same time span (Lanini and Caballero, 2016; Ollivier et al., 2020), indicating that underestimated recharge contributes substantially to the remaining area overestimation.

6.1.2 Karst-structural limitations

800 A simplified, mass-conserving, single-outlet water balance cannot represent several characteristic features of karst groundwater systems. Recharge within a delineated catchment may discharge through multiple outlets, such that the area inferred from the simplified water balance represents only a minimum catchment size and may underestimate the hydrogeologically delineated catchment (Goldscheider, 2010). This likely explains some of the strongest underestimations. For example, tracer tests indicate diversion of recharge from the Poltarica system (SI-0042) towards Krka spring and other springs in the Krka Valley (Slove-
805 nian Environment Agency, 2026). Similarly, for the Source de la Birse (CH-0001), the ERA5-Land-based recharge estimate (869 mm) agrees closely with the regional estimate of 883 mm by Malard et al. (2016). Since tracer tests indicate overlapping catchments (Schindler, 1977), the observed 72 % area underestimation is more likely related to the hydrogeological complexity of the system than to bias in the recharge estimate.

Conversely, groundwater inflow from deep regional systems can cause catchment area to be overestimated because the
810 water-balance approach attributes the resulting additional discharge to recharge within the catchment. For the Blaue Quelle (AT-0020), whose area is overestimated by 340 %, relatively constant temperature, discharge, and hydrochemistry indicate a substantial contribution from deep groundwater (BMLFUW, 2005).



Moreover, karst recharge areas are not necessarily fixed: groundwater divides can shift with hydrological conditions (Ravbar and Goldscheider, 2007), while groundwater exchange, overflow, deep regional flow, and features such as estavelles can further alter the area contributing to a spring (Goldscheider, 2010, 2005). The proposed approach cannot resolve these temporal and structural dynamics.

6.2 Uncertainties in catchment orientation and geometry

The geometric mismatches between the approximated and expert-based catchments arise primarily from limitations of the topographic proxy used for orientation and the imposed circular geometry.

6.2.1 Limitations of topography-based orientation

The orientation of the approximated catchment relies on a topographically derived drainage network and therefore assumes that surface topography provides information on the dominant groundwater-flow direction. This assumption can fail where karst drainage is decoupled from surface drainage. Where a spring lacks a representative surface drainage network, the DEM may yield only a small local catchment or associate the spring with an unrelated nearby stream, resulting in erroneous orientation. Schreiende Brunnen (AT-0014) and Etzbachquelle (AT-0063) illustrate these respective cases. In low-relief settings, such as the poljes of Slovenia, small elevation gradients can likewise prevent the derivation of a stable topographic catchment (e.g. Unica, SI-0035).

A more fundamental limitation occurs where groundwater flow crosses topographic divides or is controlled primarily by geological structure. For the Source de la Birse (CH-0001), for example, the karst catchment extends beyond the surface watershed (Schindler, 1977). The Obwald (AT-0060) and Fidelis (AT-0037) springs represent a more extreme case: groundwater is routed eastward through the karstified Sulzfluh limestones beneath the overlying Silvretta nappe, placing the recharge area several kilometres west of the springs (Mathis, 2005) (Fig. 4b). Such settings cannot be captured by an orientation derived from local surface topography and explain why apparently plausible estimates of area and orientation do not necessarily result in spatial overlap.

Overall, topography cannot fully represent karst groundwater-flow direction because subsurface drainage may cross or even oppose topographic gradients (Goldscheider, 2010; Ford and Williams, 2007a).

6.2.2 Limitations of the geometric approximation

Even where catchment size and orientation are represented adequately, the imposed circular geometry limits the achievable spatial agreement with irregular or elongated karst catchments. This limitation is reflected in the significant relationship between expert-catchment circularity and IoU (Fig. 5c). The circular approximation is therefore intended to represent the approximate location and spatial extent of the recharge area rather than its actual boundary.



6.3 Uncertainty in expert-based reference catchments

The evaluation of both recharge-area size and geometric agreement assumes that the expert-based catchments provide an appropriate reference. However, these delineations are themselves uncertain because their extent depends on the available tracer tests, sampled hydrological conditions, and auxiliary hydrogeological information. For example, for the Moosbrunnquelle (AT-0023), an independent area estimate of 9.4 km^2 derived from the mean specific discharge reported by Probst et al. (2003) is closer to our approximation ($A(C_A) = 7 \text{ km}^2$) than to the expert reference ($A(C_E) = 1.5 \text{ km}^2$) of Masten et al. (2026). Differences between C_A and C_E therefore cannot always be attributed solely to errors in the proposed approach.

This uncertainty is compounded by the fact that the hydrological conditions underlying the expert-based delineations are not always documented. Since our water-balance approach yields a mean recharge area for the available hydrological years, comparisons between our mean-condition approximations and expert catchments delineated under unknown conditions should not be over-interpreted.

6.4 Uncertainties in meteorological forcing and model structure

6.4.1 Meteorological forcing uncertainty

The use of different national meteorological datasets introduces heterogeneity in forcing quality and spatial resolution across the study regions. However, this is unlikely to substantially affect the comparison between catchment representations because C_E , C_A , and C_P for a given spring are derived from the same underlying meteorological dataset. Dataset-specific uncertainties therefore primarily affect comparisons among springs rather than the within-spring comparison of catchment representations. Differences in spatial resolution may nevertheless influence the sensitivity of the forcing to catchment representation. In particular, the coarser resolution of SAFRAN ($8 \text{ km} \times 8 \text{ km}$) compared with the approximately $1 \text{ km} \times 1 \text{ km}$ resolution of the other national datasets results in stronger spatial averaging and may reduce differences in meteorological forcing between catchment representations.

Meteorological forcing is further affected by uncertainties due to aggregation of temperature and the measurement and interpolation of precipitation. These uncertainties are particularly relevant in Alpine catchments, where strong elevation gradients coincide with a comparatively sparse high-elevation observational network.

Catchment-mean temperature may be biased where catchment boundaries only partially overlap the relatively coarse temperature grid cells, particularly in areas of strong topographic relief. A grid-cell temperature represents conditions across the entire cell and may therefore not be representative of the portion of the cell contained within the catchment if the two differ substantially in elevation. This limitation is particularly relevant for small, high-relief catchments that comprise only a few grid cells and therefore have a large proportion of partially overlapping cells. In contrast, mean catchment elevation is derived from the substantially finer-resolution DEM (30 m), allowing the elevation of the area actually contained within the catchment to be represented more accurately.

Precipitation forcing is additionally affected by systematic gauge undercatch, particularly at high elevations. Wind deflection, evaporative losses, and wetting of gauge surfaces lead to underestimated precipitation, with errors exceeding 40 % reported for



875 wind-exposed, snow-rich sites above 1500 m a.s.l. (Sevruk, 1985). Solid precipitation is affected more strongly than rainfall
 (Grossi et al., 2017). Such measurement biases propagate into gridded precipitation products (Hiebl and Frei, 2018; Federal
 Office of Meteorology and Climatology MeteoSwiss, 2021) and are compounded by the lower density of precipitation gauges
 at high elevations (Frei, 2021; Rauthe et al., 2013). Furthermore, spatial interpolation smooths local precipitation variability
 in gridded products (Frei, 2021), which may partly explain the consistently high precipitation correlations between catchment
 880 representations observed in Sect. 4.3.2.

These forcing uncertainties can propagate directly into modelled discharge, both for KarstMod and LSTM. In particular for
 KarstMod, underestimated precipitation, especially snowfall, reduces the available water input and snow accumulation and
 may consequently contribute to underestimated snowmelt discharge and negative rBias.

6.4.2 KarstMod structure

885 Unlike hydrological modelling approaches that explicitly correct snowfall (Ruelland, 2023) or total precipitation (Girons Lopez
 et al., 2020) for gauge undercatch, KarstMod does not include a precipitation correction factor. Uncertainty in precipitation
 input may therefore be partly compensated through other calibrated components of the water balance. For example, Rispal
 et al. (2026) allowed the calibrated recharge area to exceed the expert-based delineation, providing flexibility to compensate
 for potentially underestimated precipitation in mountainous regions. In the present experimental design, recharge area was
 890 constrained to within $\pm 5\%$ of the value prescribed by each catchment representation and could therefore provide little such
 compensation. Precipitation errors may instead have been partly absorbed through other degrees of freedom in the model,
 particularly the omission or adjustment of evapotranspiration.

The snow routine introduces additional structural uncertainty. One limitation is the prescribed calibration range of the thresh-
 old temperature T_{thr} ($\pm 1^\circ\text{C}$). Comparable or more restrictive assumptions have been used in previous studies, including fixed
 895 thresholds of 0°C (Fan et al., 2020; Çallı et al., 2022; Ruelland, 2023). However, biases arising from spatial aggregation
 of gridded temperature data (Sect. 6.4.1) or the assumed temperature lapse rate may exceed the flexibility provided by this
 range. The consistently positive calibrated T_{thr} values across catchment representations (Fig. E1c,d) indicate a systematic
 tendency of the calibration to delay snowmelt relative to the supplied temperature forcing. This may represent compensation
 for temperature-related forcing uncertainty, but compensation for limitations of the snow routine itself cannot be excluded.
 900 Accordingly, Rispal et al. (2026) allowed a wider threshold-temperature range to provide additional flexibility for uncertainty
 in the altitudinal temperature gradient.

More generally, the degree-day snow routine represents snow accumulation and melt primarily as a function of air temper-
 ature. Although temperature provides a useful proxy for the energy available for snowmelt (Ohmura, 2001), several processes
 affecting the spatial distribution and timing of melt are not represented explicitly. These include redistribution of snow by wind
 905 and avalanching (Freudiger et al., 2017), as well as spatial differences in radiation associated with slope orientation, sunshine
 duration, and snow albedo. More spatially explicit approaches can account for some of these effects, for example through
 temporally varying melt factors linked to potential radiation (Ruelland, 2023). Such structural limitations provide a plausible



explanation for seasonal discharge discrepancies that occur across all catchment representations, including C_E , and therefore cannot be attributed to catchment approximation alone.

910 Calibration can compensate for some uncertainty in catchment representation and meteorological forcing, but this flexibility also limits the physical interpretation of the calibrated model structure and parameters. Similar model performance may therefore result from different combinations of forcing, recharge area, and calibrated parameters rather than from an equally accurate representation of the underlying hydrological processes.

6.4.3 Limitations of the global LSTM evaluation

915 The stronger sensitivity to catchment representation in snow-influenced catchments may partly reflect the implicit representation of snow processes within the LSTM. The model used here relies solely on precipitation and temperature as dynamic inputs and must therefore infer snow accumulation and melt from these variables. Although LSTMs can learn snow-related processes without explicit snow-state variables (Kratzert et al., 2019a; Cinkus et al., 2023), explicit representation of snow processes has been shown to improve performance of DL-models in snow-dominated catchments (Sezen et al., 2026; Xu et al., 2022; Zhong
 920 et al., 2023).

The temporal in-sample evaluation used here limits the conclusions that can be drawn about the quality of environmental static features. Because all springs evaluated during testing were also represented during training, the LSTM can potentially use static features primarily to distinguish individual springs rather than to transfer learned relationships to unseen locations. Consequently, the absence of a performance advantage for C_E -derived static features does not necessarily imply that their
 925 environmental information is no more representative than that derived from C_A or C_P . Differences in static-feature quality may become more apparent under spatial out-of-sample evaluation, where predictions are made for springs excluded from training (Liesch and Ohmer, 2026) and the model is forced to generalise. Such an evaluation is constrained here by the limited sample size ($n = 63$), as withholding springs would further reduce the training dataset. The relatively small dataset may itself limit the model's ability to learn transferable relationships from environmental attributes, given that global-model performance
 930 generally benefits from larger training datasets (Kratzert et al., 2024).

7 Conclusions

This study presents and evaluates an automated approach for karst catchment approximation from discharge, gridded recharge and topography, with the aim to provide catchment representations for applications in large-sample discharge modelling. The approach was evaluated for 63 springs across the wider Alpine region, first against expert-based catchment delineations and
 935 subsequently through its influence on discharge simulations with the lumped reservoir model KarstMod and a global LSTM.

The catchment approximation provides a useful first-order representation of recharge-area size and location, but should not be interpreted as a hydrogeological delineation. In terms of size, the estimated recharge areas show a median bias in size of 11 % relative to the expert-based delineations, with 65 % of the springs falling within $\pm 50\%$, despite substantial deviations for individual springs. Larger discrepancies can reflect uncertainty in both the water-balance inputs and the expert-based refer-



940 ence delineations, as well as karst-specific processes such as groundwater exchange, overlapping catchments, and temporally variable contributing areas that cannot be represented by a steady-state single-outlet water balance. The estimated area should therefore be interpreted as an effective mean recharge area for the observation period. Spatial agreement and orientation are more variable. While surface topography provides a scalable first-order proxy for catchment orientation, it can fail where topographic gradients and subsurface drainage indicate substantially different or opposing recharge-area orientations.

945 Despite imperfect geometric agreement, the approximated catchments represent catchment-mean elevation, precipitation, and temperature more closely than the point representation, particularly where spatial and topographic variability are pronounced. Thus, accurate reconstruction of the hydrogeological boundary is not necessarily required to improve the spatial representation of model inputs.

The consequences of these differences for modelling purposes depend strongly on model structure as well as on spring
 950 discharge seasonality. For KarstMod, the point-based representation results in a clear performance penalty, whereas models based on the approximated catchments recover the median performance achieved using expert-based catchments. Recharge-area size is an important control on the simulated water balance, although calibration can partly compensate for area and forcing errors. For snow-influenced springs, catchment elevation and the resulting temperature representation provide an additional control. By neglecting the elevation distribution in the catchment, the point representation can distort snow accumulation
 955 and melt dynamics beyond what calibration of the snow routine can compensate for. Greater flexibility in recharge area and snow-related parameters than applied within this study could partly compensate for uncertainties in meteorological forcing and improve discharge simulations. However, such flexibility increases parameter compensation and weakens the physical interpretation of calibrated quantities; similar predictive performance therefore does not necessarily imply an equally accurate representation of the underlying hydrological processes.

960 The global LSTM was substantially less sensitive to catchment representation, with the point-based representation achieving performance close to that obtained with approximated and expert-based catchments under temporal in-sample evaluation. Differences became more apparent for snow-influenced springs, suggesting that spatially representative dynamic inputs may become more relevant where elevation-dependent processes strongly affect discharge. Environmental static features provided no consistent advantage over random identifiers. Whether improved catchment representations become more important for
 965 transfer to ungauged springs would require spatial out-of-sample evaluation, which was out-of-scope for this study.

Taken together, the results demonstrate that automated catchment approximation can provide a practical basis for extending karst spring discharge modelling beyond well-investigated systems. Where reliable expert-based delineations are available, these should be preferred because they incorporate hydrogeological information that cannot be recovered from the simplified water balance and surface topography alone. The proposed approach is therefore not intended to replace expert delineation, but
 970 to provide a scalable alternative based on readily available discharge, meteorological, and topographic data where expert-based delineations are unavailable. Its value lies in providing a physically informed spatial representation that improves model inputs and lumped-parameter discharge simulations relative to extracting input data solely at the spring location.

Code and data availability. The KarstMod modelling software used in this study is freely available online (<https://hal.science/hal-02071006>). Daily discharge data for all investigated springs, together with catchment-aggregated meteorological forcing, static attributes, and expert-based reference catchment delineations, are available through the ALPAKAS dataset on Zenodo (<https://doi.org/10.5281/zenodo.19329694>). The code used to derive the automated catchment approximations and to implement and evaluate the global LSTM models is publicly available in a dedicated repository at https://github.com/PaulineThinius/Catchment_approx.

Appendix A: Static features

Table A1. Static catchment descriptors used as inputs to the global LSTM. For expert-derived catchments, descriptors were obtained directly from the ALPAKAS dataset. For catchment approximations, descriptors were derived following the same methodology as described by Joger et al. (2026a) using the listed data sources. For the naive point representation, static descriptors were taken from the grid cell containing the spring location.

Domaine	Description	Unit	Data source
General	Station longitude (EPSG:4326)	°	ALPAKAS (Joger et al., 2026b)
	Station latitude (EPSG:4326)	°	
	Catchment area ^a	km ²	
Topography	Mean elevation within catchment	m a.s.l.	GLO-30 (ESA, 2022)
	Minimum elevation within catchment	m a.s.l.	
	Maximum elevation within catchment	m a.s.l.	
	Mean slope within catchment	°	
	Percentage of catchment area with slope smaller than 3°	%	
	Percentage of catchment area with slope greater than 15°	%	
	Mean northness within catchment as the average cosine of terrain aspect	-	
	Mean eastness within catchment as the average sine of terrain aspect	-	
Land use	Percentage of agriculture	%	CLC 2018 (EEA, 2020)
	Percentage of wetland	%	
	Percentage of urban and settlements	%	
	Percentage of loose and hard rocks and bare soils	%	
	Percentage of forest	%	
	Percentage of grass and herbs and medium-scale vegetation	%	
Climate	Köppen-Geiger climate classification at the station location	-	Beck et al. (2023)
Hydrogeology	Percentage of highly productive porous aquifers	%	IHME1500 (BGR and UNESCO, 2019)
	Percentage of low and moderately productive porous aquifers	%	
	Percentage of highly productive fissured aquifers	%	
	Percentage of low and moderately productive fissured aquifers	%	
	Percentage of locally aquiferous rocks	%	
	Percentage of practically non-aquiferous rocks, porous or fissured	%	

^a The catchment area is sourced from the ALPAKAS dataset for C_E . For C_A and C_P , the approximated catchment area is derived using the method described in Sect. 3.1.1.



Appendix B: Topographic catchment refinement

980 To avoid snapping stations to nearby higher-order channels or failing to identify a suitable local stream, the plausibility of the snapped location was evaluated against the recharge area estimated from the water balance and the stream network was iteratively refined where necessary.

Stream cells were initially defined using a minimum flow-accumulation threshold of $acc_{thr} = 1000$ DEM cells. Each station was snapped to the nearest stream cell within a maximum search distance of 180 m.

985 The flow accumulation at the snapped location ($acc_{current}$) was evaluated against the expected accumulation:

$$acc_{expected} = \frac{A}{A_{DEM-cell}}, \quad (B1)$$

where A is the recharge area estimated in Sect. 3.1.1 and $A_{DEM-cell}$ is the area of one DEM cell. Thus, $acc_{expected}$ represents the estimated recharge area expressed as an equivalent number of contributing DEM cells. If $acc_{current} > 3 \cdot acc_{expected}$, indicating potential snapping to a substantially larger neighbouring channel, or if no stream cell was identified within the snapping
 990 distance, the stream definition was iteratively refined. A tolerance factor of three was adopted to allow for uncertainty in station location and DEM-derived flow routing while still preventing snapping to substantially larger neighbouring channels.

During each iteration, acc_{thr} was halved, thereby increasing the density of the extracted stream network and allowing smaller local channels to be considered during snapping. Stream extraction and snapping were then repeated until $acc_{current} \leq 3 \cdot acc_{expected}$ or acc_{thr} reached the minimum value of one contributing cell. The final snapped location was used as the outlet
 995 for watershed delineation.

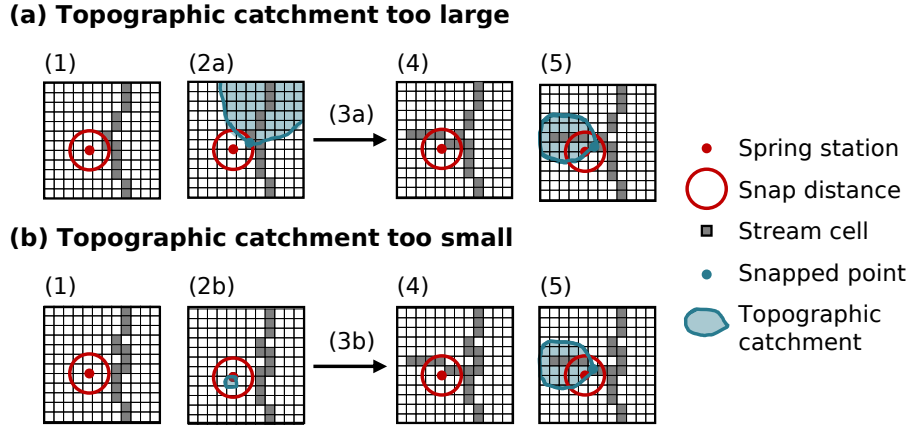


Figure B1. Schematic illustration of the topographic catchment refinement procedure for two failure cases. (a) A catchment that is unrealistically large because the station is initially snapped to a nearby higher-order stream. (b) A catchment that is unrealistically small because no stream cell is identified within the maximum snapping distance. The numbered panels indicate the refinement sequence: (1) initial stream network derived using the initial accumulation threshold (acc_{thr}); (2a) snapping of the station to the nearest stream cell within the search distance, or (2b) failure to identify a stream cell within the search distance; (3a) evaluation of the snapped flow accumulation against the expected accumulation, indicating a potential mismatch with a higher-order channel, or (3b) identification of an unrealistically small catchment resulting from the absence of a suitable stream cell; (4) redefinition of the stream network using a reduced accumulation threshold; and (5) final snapping and watershed delineation. The threshold reduction may be repeated iteratively until a suitable snapped location is obtained.

Appendix C: Data split

Table C1: Data split used for KarstMod and the global LSTM for each spring. KarstMod uses a warm-up and calibration period, whereas the global LSTM uses training and validation periods; both models share the same test period. Percentages indicate discharge data availability within the respective calibration, training, validation, and test periods.

ALPA-KAS ID	KarstMod			Global LSTM				KarstMod + Global LSTM		
	warmup start	calibration start	[%]	training start	[%]	validation start	[%]	testing start	testing end	[%]
AT-0001	01.10.1989	10.08.1995	97	10.08.1995	98	01.01.2020	94	01.01.2022	31.12.2023	100
AT-0004	01.10.1992	01.01.1998	93	01.01.1998	93	01.01.2020	95	01.01.2022	31.12.2023	82
AT-0005	01.10.1974	01.06.1980	100	01.06.1980	100	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0006	01.10.1985	01.01.1991	100	01.01.1991	100	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0007	01.10.1970	01.01.1976	100	01.01.1976	100	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0008	01.10.1991	01.01.1997	96	01.01.1997	96	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0009	01.10.1993	01.01.1999	100	01.01.1999	100	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0010	01.10.1992	01.01.1998	91	01.01.1998	90	01.01.2020	100	01.01.2022	31.12.2023	100



AT-0011	01.10.2000	01.01.2006	100	01.01.2006	100	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0012	01.10.2009	16.06.2015	100	16.06.2015	100	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0013	01.10.1991	03.01.1997	96	03.01.1997	96	01.01.2020	100	01.01.2022	31.12.2023	85
AT-0014	01.10.1992	01.01.1998	92	01.01.1998	92	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0015	01.10.1986	01.01.1992	90	01.01.1992	89	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0018	01.10.1993	12.09.1999	92	12.09.1999	92	19.08.2016	95	19.08.2018	18.08.2020	100
AT-0019	01.10.2002	14.07.2008	96	14.07.2008	95	04.11.2016	100	04.11.2018	03.11.2020	100
AT-0020	01.10.1986	27.08.1992	94	27.08.1992	93	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0021	01.10.1993	16.09.1999	93	16.09.1999	92	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0022	01.10.1994	01.01.2000	96	01.01.2000	95	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0023	01.10.1994	01.07.2000	93	01.07.2000	99	01.01.2020	29	01.01.2022	31.12.2023	94
AT-0024	01.10.1997	01.01.2003	95	01.01.2003	95	01.01.2019	98	01.01.2021	31.12.2022	100
AT-0025	01.10.2002	15.11.2007	93	15.11.2007	91	01.01.2019	100	01.01.2021	31.12.2022	97
AT-0026	01.10.2002	01.01.2008	96	01.01.2008	98	30.07.2015	92	30.07.2017	29.07.2019	98
AT-0027	01.10.1989	01.02.1995	82	01.02.1995	82	01.01.2019	72	01.01.2021	31.12.2022	94
AT-0029	01.10.1990	01.01.1996	92	01.01.1996	91	01.01.2019	100	01.01.2021	31.12.2022	87
AT-0030	01.10.1993	01.07.1999	88	01.07.1999	87	01.01.2019	100	01.01.2021	31.12.2022	98
AT-0033	01.10.2006	24.09.2012	96	24.09.2012	94	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0035	01.10.1990	01.01.1996	88	01.01.1996	87	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0037	01.10.1992	01.01.1998	90	01.01.1998	89	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0038	01.10.1993	01.01.1999	84	01.01.1999	82	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0039	01.10.1994	24.05.2000	75	24.05.2000	73	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0040	01.10.1991	01.07.1997	97	01.07.1997	98	08.10.2009	95	08.10.2011	07.10.2013	100
AT-0041	01.10.1989	01.01.1995	98	01.01.1995	98	01.01.2019	100	01.01.2021	31.12.2022	100
AT-0043	01.10.1991	01.01.1997	99	01.01.1997	99	01.01.2019	100	01.01.2021	31.12.2022	100
AT-0046	01.10.1993	17.04.1999	98	17.04.1999	98	01.01.2019	100	01.01.2021	31.12.2022	100
AT-0053	01.10.1997	01.01.2003	93	01.01.2003	93	01.01.2017	92	01.01.2019	31.12.2020	86
AT-0055	01.10.2004	01.07.2010	97	01.07.2010	96	01.01.2017	100	01.01.2019	31.12.2020	100
AT-0056	01.10.2001	01.01.2007	84	01.01.2007	82	01.01.2017	90	01.01.2019	31.12.2020	90
AT-0058	01.10.2003	23.10.2008	95	23.10.2008	96	01.01.2019	90	01.01.2021	31.12.2022	100
AT-0060	01.10.2002	23.01.2008	100	23.01.2008	100	01.01.2020	100	01.01.2022	31.12.2023	100
AT-0062	01.10.2005	14.07.2011	100	14.07.2011	100	01.01.2019	100	01.01.2021	31.12.2022	100
AT-0063	01.10.2008	01.01.2014	100	01.01.2014	100	01.01.2019	100	01.01.2021	31.12.2022	100
CH-0001	01.10.1975	02.01.1981	100	02.01.1981	100	04.10.2002	100	04.10.2004	03.10.2006	100
CH-0004	01.01.1971	01.01.1974	100	01.01.1974	100	01.01.2021	100	01.01.2023	31.12.2024	100
CH-0005	01.10.1982	11.05.1988	100	11.05.1988	100	01.12.2020	100	01.12.2022	30.11.2024	100
CH-0006	01.10.1993	14.04.1999	95	14.04.1999	95	25.08.2019	100	25.08.2021	24.08.2023	100
CH-0008	01.10.2003	26.02.2009	100	26.02.2009	100	01.01.2021	100	01.01.2023	31.12.2024	100
CH-0010	01.10.1997	14.05.2003	97	14.05.2003	97	01.01.2021	98	01.01.2023	31.12.2024	98
CH-0012	01.10.1998	30.10.2003	100	30.10.2003	100	01.01.2021	100	01.01.2023	31.12.2024	100
CH-0016	01.10.1994	01.01.2000	97	01.01.2000	96	01.01.2021	100	01.01.2023	31.12.2024	98
CH-0018	01.10.2004	18.06.2010	98	18.06.2010	98	14.12.2020	99	14.12.2022	13.12.2024	100
CH-0026	01.10.1986	24.09.1992	16	24.09.1992	12	01.01.2013	50	01.01.2015	31.12.2016	100
DE-0015	01.01.1951	01.11.1955	99	01.11.1955	100	01.01.2021	99	01.01.2023	31.12.2024	92



DE-0019	01.10.2007	16.01.2013	100	16.01.2013	100	01.01.2021	100	01.01.2023	31.12.2024	95
FR-0007	01.10.1978	15.10.1983	91	15.10.1983	90	02.01.2020	100	02.01.2022	01.01.2024	98
FR-0011	01.10.1970	29.09.1976	97	29.09.1976	97	02.01.2020	99	02.01.2022	01.01.2024	88
FR-0013	01.10.1963	21.02.1969	99	21.02.1969	99	02.01.2020	100	02.01.2022	01.01.2024	100
FR-0024	01.10.1960	02.01.1966	100	02.01.1966	100	02.01.2020	100	02.01.2022	01.01.2024	100
FR-0034	01.10.2008	01.10.2013	79	01.10.2013	72	13.12.2019	100	13.12.2021	12.12.2023	100
SI-0012	01.10.1999	29.09.2005	83	29.09.2005	86	01.01.2015	73	01.01.2017	31.12.2018	100
SI-0016	01.01.1950	01.01.1950	99	01.01.1950	99	01.01.2015	100	01.01.2017	31.12.2018	100
SI-0035	01.10.1955	01.01.1961	82	01.01.1961	100	01.01.1970	0	01.01.1972	31.12.1973	100
SI-0038	01.10.1955	01.01.1961	93	01.01.1961	93	01.01.2015	100	01.01.2017	31.12.2018	100
SI-0042	01.01.1950	01.01.1955	43	01.01.1955	41	01.01.2015	92	01.01.2017	31.12.2018	54

Appendix D: Validation Part I: Geometry, static and dynamic catchment characteristics

D1 Geometric validation metrics

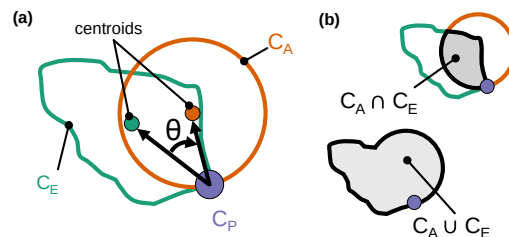


Figure D1. (a) Concept of the angle between centroids and spring for expert-based catchment C_E and approximated catchment C_A (b) Intersection and union of C_A and C_E as required for the computation of the IoU



D2 Convergence of the recharge-area estimate

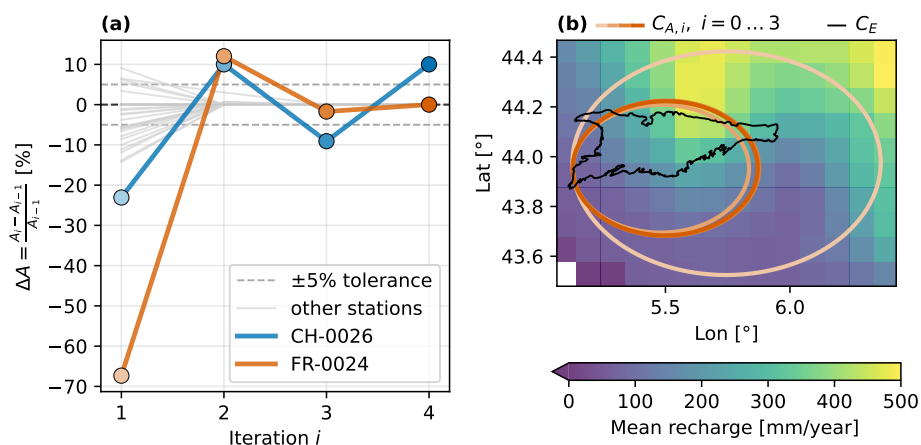


Figure D2. (a) Change in estimated recharge area over iterations of the catchment estimation process for all stations and (b) influence of iterations on catchment approximation for Source de la Sorgue (FR-0024). The circular C_A geometries appear elliptical because the maps are displayed in geographic (longitude/latitude) coordinates.

1000 D3 Catchment validation metrics for individual springs



Table D1. Validation I: geometry and static/dynamic catchment characteristics. The reference catchment C_E gives observed discharge ($\bar{Q}$), area (A), mean elevation ($\bar{z}$) and elevation range (z_{range}); the approximated (C_A) and point-based (C_P) representations are compared to C_E through the listed geometric, elevation, precipitation and temperature metrics (geometry for C_A only). All Δ values are approximation minus reference. Symbols and methods are defined in Sect. 3.2.

		Reference catchment				Validation Part I: Geometry, static and dynamic catchment characteristics											
		C_E		C_A		C_P											
ALPA- KAS ID	spring name	$\bar{Q}^a$ l s ⁻¹	A^a km ²	$\bar{z}^a$ m asl	z_{range}^a m	ΔA %	θ °	IoU	$\Delta \bar{z}$ m	r_P -	ΔP mm	$\Delta \bar{T}$ °C	$\Delta \bar{z}$ m	r_P -	ΔP mm	$\Delta \bar{T}$ °C	
AT-0001	Teufelskirche	967	19.2	1303	1249	+61	28	0.37	-226	1.00	-45	0.8	-536	1.00	-122	+2.5	
AT-0004	Steyernquelle	277	8.2	1158	954	+22	23	0.47	-150	1.00	-60	0.7	-462	1.00	-145	+2.5	
AT-0005	Pießling Ursprung	2170	34.7	1648	1579	+62	6	0.55	-52	1.00	-22	0.2	-843	1.00	-231	+3.7	
AT-0006	Rettenbachquelle	1065	25.3	1367	1347	+34	23	0.44	-136	1.00	+23	+0.5	-619	1.00	-298	+3.0	
AT-0007	Quelle Brunntal	381	7.5	1055	963	+73	33	0.34	-28	1.00	-18	+0.0	-489	0.99	-105	+1.9	
AT-0008	Miesenbachursprung	787	11.6	1312	1386	+115	6	0.46	-1	1.00	-14	+0.0	-876	1.00	-176	+3.7	
AT-0009	Gollinger Wasserfall	1235	17.4	1556	1978	+49	24	0.46	-353	1.00	-83	+1.2	-649	1.00	-349	+4.3	
AT-0010	Marbachquelle	437	14.4	1924	1514	-10	4	0.56	-186	1.00	-34	+0.9	-692	0.99	-231	+3.2	
AT-0011	Dachserfall	964	27.0	1977	1612	-15	5	0.58	-109	1.00	-19	+0.5	-1196	1.00	-156	+2.0	
AT-0012	Schwarze Torrenquelle	1182	25.0	1845	1745	+8	10	0.42	-178	1.00	-59	+0.8	-1150	0.98	-401	+5.7	
AT-0013	Schwarzlackenquelle	224	3.7	1822	1167	+37	51	0.23	-311	1.00	-78	+1.2	-317	1.00	-265	+2.9	
AT-0014	Schreiende Brunnen	79	1.6	1705	1066	+26	120	0.00	-416	1.00	-165	+1.4	-319	1.00	-187	+1.7	
AT-0015	Stubbachquelle	90	1.3	1672	1313	+60	2	0.51	-69	1.00	-34	+0.2	-623	1.00	-343	+4.6	
AT-0018	Lehnbachquellen	61	1.0	1658	729	-2	8	0.67	-71	1.00	-22	+0.3	-576	1.00	-127	+1.7	
AT-0019	Schwarzbodenquelle	31	0.4	1410	524	+138	17	0.41	+105	1.00	+23	-0.4	-316	1.00	+20	-0.4	
AT-0020	Blaue Quelle	718	4.3	825	558	+344	6	0.23	-52	1.00	+12	+0.1	-303	1.00	-179	+1.7	
AT-0021	Pulvermühlquelle	81	3.1	1601	929	-36	28	0.39	-248	1.00	-87	+1.0	-300	1.00	-142	+2.9	
AT-0022	Auebachquelle	35	0.5	1403	624	+76	18	0.32	-153	1.00	-66	+0.7	-259	1.00	-168	+1.8	
AT-0023	Moosbrunnquelle	208	1.5	1306	1260	+382	40	0.20	+65	1.00	+60	-0.6	-730	1.00	-242	+2.8	
AT-0024	Ursprungquelle (Lehnberg)	116	2.9	2065	1028	+3	36	0.37	+12	1.00	+42	-0.2	-484	1.00	-30	+0.6	

^a Data obtained from the ALPAKAS dataset (Joger et al., 2026b).



		Reference catchment				Validation Part I: Geometry, static and dynamic catchment characteristics										
ALPA- KAS ID	spring name	C_E				C_A				C_P						
		$\overline{Q}^a$ l s ⁻¹	A^a km ²	$\overline{z}^a$ m asl	z_{range}^a m	ΔA %	θ °	IoU	$\Delta \overline{z}$ m	r_P -	ΔP mm	$\Delta \overline{T}$ °C	ΔP mm	$\Delta \overline{T}$ °C		
AT-0025	Siebenbrunnenquelle	96	1.3	1914	877	+53	35	0.29	-186	1.00	+12	+0.6	-228	1.00	-84	+2.2
AT-0026	Lastal-Stollenquelle	67	1.6	1493	965	-38	57	0.04	-359	1.00	-146	+1.4	-125	1.00	-164	+1.5
AT-0027	Große Mühlquelle	507	9.4	1061	1346	+102	7	0.42	-122	1.00	-19	+0.4	-399	1.00	-120	+1.9
AT-0029	Reithbachquelle	238	6.2	945	782	+45	49	0.25	-32	1.00	-17	+0.0	-352	1.00	+50	+1.1
AT-0030	Steinbachquelle	473	10.6	984	849	+79	4	0.55	-121	1.00	-18	+0.4	-363	1.00	-42	+2.1
AT-0033	Fellbachquelle	230	7.0	1344	826	+14	30	0.43	-54	1.00	+1	+0.0	-401	1.00	-20	-0.2
AT-0035	Gerstenbödenquelle	33	0.8	1498	659	+11	7	0.44	-144	1.00	-20	+0.5	-271	1.00	-29	+1.0
AT-0037	Fidelisquelle	292	6.4	2284	662	+10	34	0.00	-536	1.00	+37	+2.1	-459	1.00	+11	+5.6
AT-0038	Aubachquelle	943	28.9	1613	1162	-27	1	0.53	-118	1.00	-89	+0.5	-419	1.00	-293	+2.2
AT-0039	Marulbachquelle	255	2.9	1885	1094	+110	8	0.24	-204	1.00	-36	+0.9	-636	1.00	-106	+3.0
AT-0040	Roßlochquelle	379	13.8	1282	839	+16	4	0.41	-119	1.00	-18	+0.5	-343	0.99	-91	+1.6
AT-0041	Hammerbachquelle	182	19.9	818	606	-15	41	0.19	-118	1.00	-37	+0.5	-290	1.00	-80	+1.8
AT-0043	Wassermannsloch	478	32.4	1465	1381	-48	2	0.17	-285	1.00	-151	+1.3	-595	0.99	-262	+2.4
AT-0046	Schwabeltalquelle	101	2.6	1498	1094	+13	2	0.38	-254	1.00	-22	+0.6	-444	1.00	-67	+2.5
AT-0053	Alfützquelle	139	1.5	1571	643	+102	96	0.01	+210	1.00	-127	-0.1	-526	1.00	-152	+1.1
AT-0055	Eibachquelle	391	9.2	2012	1462	-2	17	0.26	-150	1.00	-113	+0.8	-541	0.98	-330	+3.3
AT-0056	Heiterwandquelle	152	0.6	2146	953	+533	3	0.16	-85	1.00	+21	-0.1	-461	1.00	-21	+1.1
AT-0058	Oswaldquelle	47	1.5	1638	838	+34	3	0.46	-90	1.00	+13	+0.5	-347	1.00	+50	+1.6
AT-0060	Obwaldquelle	111	2.0	2400	696	+50	18	0.00	-349	1.00	+10	+1.4	-374	1.00	-13	+2.6
AT-0062	Pöllauer Ursprung	97	4.7	1542	734	+28	0	0.57	-49	1.00	-3	+0.2	-342	1.00	-47	+1.4
AT-0063	Eitzbachquelle	147	7.2	1573	1142	-30	52	0.09	-267	0.99	-13	+1.0	-426	0.98	-31	+2.8
CH-0001	Source de la Birse	197	25.0	1035	506	-72	139	0.07	-29	0.99	-3	+0.3	-255	0.99	-48	+0.8
CH-0004	Source de l'Areuse	4800	138.7	1120	500	+2	52	0.36	-71	1.00	-12	+0.2	-297	0.99	-46	+1.5

^a Data obtained from the ALPAKAS dataset (Joger et al., 2026b).



		Reference catchment				Validation Part I: Geometry, static and dynamic catchment characteristics											
		C_E		C_A		C_P											
ALPA- KAS ID	spring name	$\bar{Q}^a$ l s ⁻¹	A^a km ²	$\bar{z}^a$ m asl	z_{range}^a m	ΔA %	θ °	IoU	$\Delta \bar{z}$ m	r_P -	ΔP mm	$\Delta \bar{T}$ °C	$\Delta \bar{z}$ m	r_P -	ΔP mm	$\Delta \bar{T}$ °C	
CH-0005	Schlichen Brünnen	1972	39.5	1706	1697	-1	47	0.20	-276	1.00	+18	+1.3	-792	0.99	+56	+4.7	
CH-0006	Source Bossy	34	1.0	903	498	-1	10	0.55	+24	1.00	+2	-0.0	-247	1.00	+12	+1.0	
CH-0008	Source de la Lionne	493	16.9	1340	411	+6	35	0.31	+19	1.00	-32	-0.0	-319	1.00	-186	+0.7	
CH-0010	Source de la Doux	26	1.2	539	252	-19	5	0.50	-42	1.00	-25	+0.1	-55	1.00	-47	+0.2	
CH-0012	Felsenquelle	5	0.3	533	111	+10	40	0.22	-19	1.00	-2	+0.1	-73	1.00	-4	+0.2	
CH-0016	Hammerrainquelle	26	2.6	1000	732	-61	36	0.14	-240	1.00	-3	+0.7	-150	1.00	+3	+1.1	
CH-0018	Source de la Dou	1229	50.8	1096	579	+10	8	0.22	-3	1.00	+5	-0.1	-365	1.00	-62	+0.8	
CH-0026	Milandre karst system	272	15.8	534	270	-30	47	0.15	-57	1.00	-9	+0.2	-84	1.00	-31	+0.5	
DE-0015	Blautopf	2327	183.4	758	366	-20	24	0.44	-45	0.99	-61	+0.1	-201	0.93	-76	+0.5	
DE-0019	Hüttenbachquelle	666	87.2	550	226	+9	34	0.37	-12	0.98	-26	+0.0	-145	0.95	-36	+0.4	
FR-0007	Source d'Arcier	1159	153.2	451	446	-63	5	0.30	-16	1.00	-15	+0.1	-189	0.94	-134	+0.5	
FR-0011	Source du Lison	5084	138.0	720	537	+12	21	0.55	+28	1.00	-6	-0.1	-364	0.95	-158	+0.9	
FR-0013	Source du Verneau	443	17.2	745	510	-1	32	0.21	-141	1.00	-41	+0.4	-238	0.96	+83	-0.7	
FR-0024	Source de la Sorgue	17322	1161.9	881	1824	+141	21	0.36	-261	1.00	-89	+1.1	-511	0.94	-253	+3.0	
FR-0034	Source du Grand Bief	1236	36.7	721	607	+31	18	0.28	-48	1.00	-20	+0.2	-303	1.00	-17	+0.2	
SI-0012	Bilpa	2645	61.3	518	660	+99	67	0.04	+99	0.97	+65	-0.6	-421	0.96	+69	+1.1	
SI-0016	Ljubljana	23683	1122.7	723	1326	-20	6	0.52	-44	1.00	-52	+0.2	-394	0.94	-133	+2.2	
SI-0035	Unica	17179	820.9	777	1343	-42	95	0.16	-122	0.96	-165	+1.0	-121	0.97	-87	+1.1	
SI-0038	Malenščica	6403	726.0	799	1343	-69	2	0.26	-82	0.99	-68	+0.4	-272	0.95	-79	+1.6	
SI-0042	Poltarica	1311	330.5	528	699	-80	17	0.20	-61	1.00	-67	+0.3	-199	0.98	-86	+0.7	

^a Data obtained from the ALPAKAS dataset (Joger et al., 2026b).

Appendix E: Validation Part II: Model performance results

E1 Detailed model performance metrics for all springs

Table E1: Performance metrics for the testing period of the KarstMod models for the three catchment representations, C_E , C_A and C_P , across all springs. Springs are grouped by seasonality cluster, and median values are reported for each cluster as well as across all springs. The best-performing catchment representation for each spring and metric is shown in bold.

	ALPAKAS ID	KGE			NSE			rBias			VE			r		
		C_E	C_A	C_P	C_E	C_A	C_P	C_E	C_A	C_P	C_E	C_A	C_P	C_E	C_A	C_P
weak seasonality	AT-0015	0.65	0.52	0.30	0.06	-0.73	-1.17	-0.08	0.15	0.14	0.89	0.80	0.79	0.74	0.72	0.65
	AT-0018	0.56	0.54	0.50	0.53	0.48	0.37	-0.15	-0.18	-0.23	0.79	0.77	0.74	0.80	0.78	0.75
	AT-0019	0.46	0.75	0.66	-5.34	0.33	0.08	-0.46	-0.11	-0.09	0.54	0.87	0.86	0.86	0.83	0.67
	AT-0020	0.04	0.72	0.61	-10.35	0.68	-0.40	-0.62	0.01	-0.17	0.38	0.91	0.82	0.47	0.83	0.66
	AT-0023	0.10	0.70	0.67	-6.16	0.75	0.58	-0.70	0.01	0.10	0.30	0.91	0.86	0.87	0.88	0.85
	AT-0033	0.51	0.60	0.55	0.50	0.62	0.55	-0.35	-0.27	-0.31	0.64	0.70	0.67	0.91	0.91	0.90
	AT-0041	0.56	0.46	0.34	0.41	0.34	0.18	-0.11	-0.08	-0.09	0.76	0.73	0.69	0.68	0.60	0.48
	AT-0053	0.31	0.72	0.62	-6.49	-0.08	-0.58	-0.56	-0.19	-0.23	0.44	0.81	0.77	0.85	0.89	0.80
	AT-0056	0.47	0.87	0.77	-20.03	-0.28	0.44	-0.41	0.10	0.05	0.59	0.90	0.95	0.88	0.92	0.83
	AT-0058	0.52	0.83	0.83	-0.06	0.56	0.55	0.14	-0.13	-0.11	0.79	0.87	0.86	0.57	0.91	0.88
	AT-0062	0.59	0.64	0.63	0.44	0.47	0.50	0.09	0.24	0.12	0.57	0.61	0.63	0.68	0.78	0.73
	CH-0006	0.74	0.76	0.75	-0.38	-0.87	-0.50	-0.11	-0.14	-0.12	0.89	0.86	0.88	0.86	0.87	0.85
	CH-0010	0.52	0.55	0.54	0.08	-1.77	-2.21	-0.13	-0.32	-0.35	0.83	0.68	0.65	0.87	0.84	0.83
	CH-0016	0.82	0.85	0.81	0.57	0.47	0.42	-0.05	-0.09	-0.09	0.92	0.89	0.89	0.85	0.91	0.90
	DE-0019	0.55	0.47	0.29	0.04	-0.30	-0.78	0.18	0.22	0.24	0.81	0.77	0.76	0.90	0.90	0.88
	SI-0038	0.82	0.91	0.89	0.70	0.84	0.79	0.14	0.04	0.05	0.79	0.85	0.83	0.90	0.92	0.90
Median		0.54	0.71	0.63	0.05	0.40	0.28	-0.12	-0.09	-0.09	0.77	0.83	0.80	0.86	0.88	0.83
pluvial	CH-0001	0.66	0.68	0.63	0.64	0.59	0.60	-0.23	-0.26	-0.27	0.68	0.67	0.67	0.86	0.85	0.86
	CH-0004	0.85	0.84	0.87	0.85	0.85	0.78	-0.09	-0.09	-0.07	0.74	0.73	0.69	0.93	0.93	0.89
	CH-0008	0.81	0.77	0.71	0.69	0.65	0.56	0.06	0.08	0.11	0.59	0.57	0.54	0.87	0.86	0.84
	CH-0012	0.87	0.85	0.85	0.78	0.76	0.77	0.05	0.06	0.06	0.85	0.84	0.85	0.91	0.90	0.91
	CH-0018	0.82	0.81	0.81	0.83	0.82	0.78	-0.16	-0.18	-0.17	0.75	0.75	0.73	0.93	0.93	0.91
	CH-0026	0.82	0.68	0.67	0.84	0.75	0.73	-0.10	-0.22	-0.21	0.72	0.61	0.60	0.92	0.89	0.88
	DE-0015	0.85	0.71	0.65	0.82	0.58	0.45	-0.07	-0.22	-0.25	0.78	0.65	0.62	0.93	0.83	0.77
	FR-0007	0.89	0.88	0.85	0.83	0.81	0.77	0.04	0.05	-0.09	0.68	0.69	0.66	0.92	0.92	0.89
	FR-0011	0.80	0.73	0.88	0.84	0.84	0.84	0.14	0.15	0.09	0.70	0.73	0.68	0.94	0.96	0.92
	FR-0013	0.86	0.82	0.81	0.82	0.81	0.78	0.04	0.01	0.15	0.63	0.62	0.56	0.91	0.90	0.89
	FR-0024	0.72	0.58	0.48	0.57	0.40	0.07	0.07	0.17	0.31	0.66	0.62	0.54	0.85	0.85	0.79
	FR-0034	0.54	0.65	0.64	0.71	0.79	0.78	-0.32	-0.26	-0.27	0.57	0.66	0.65	0.91	0.92	0.92
	SI-0012	0.57	0.84	0.69	0.60	0.71	0.56	-0.19	-0.02	0.21	0.41	0.52	0.40	0.79	0.85	0.82
	SI-0016	0.90	0.94	0.85	0.87	0.89	0.73	-0.01	0.00	0.05	0.75	0.78	0.61	0.93	0.94	0.86



	SI-0035	0.85	0.80	0.81	0.79	0.73	0.69	-0.05	-0.15	0.01	0.69	0.63	0.61	0.91	0.88	0.87
	SI-0042	0.60	0.45	0.37	0.69	0.50	0.37	0.18	0.23	0.29	0.67	0.59	0.55	0.94	0.93	0.92
	Median	0.82	0.79	0.76	0.80	0.76	0.73	-0.03	-0.01	0.03	0.69	0.65	0.61	0.91	0.90	0.88
nivo-pluvial	AT-0001	0.63	0.63	0.50	0.51	0.37	0.05	-0.06	0.21	0.26	0.46	0.33	0.18	0.72	0.69	0.58
	AT-0004	0.50	0.51	0.48	0.44	0.35	0.07	-0.15	-0.02	0.08	0.28	0.23	0.10	0.66	0.60	0.49
	AT-0006	0.74	0.72	0.55	0.50	0.44	0.03	0.05	0.05	0.09	0.54	0.51	0.32	0.75	0.72	0.57
	AT-0007	0.78	0.40	0.43	0.58	0.18	0.01	0.01	0.46	0.39	0.54	0.35	0.29	0.78	0.80	0.71
	AT-0008	0.56	0.67	0.52	0.55	0.49	0.11	-0.23	-0.19	-0.22	0.52	0.50	0.33	0.77	0.74	0.57
	AT-0021	0.71	0.72	0.49	0.48	0.52	-0.09	0.13	0.01	0.33	0.69	0.73	0.50	0.75	0.74	0.62
	AT-0022	0.53	0.67	0.61	0.36	0.50	0.46	-0.02	0.05	0.03	0.50	0.57	0.53	0.61	0.72	0.68
	AT-0026	0.75	0.45	0.42	0.69	0.38	0.34	-0.18	-0.36	-0.36	0.69	0.55	0.54	0.86	0.77	0.75
	AT-0027	0.52	0.68	0.55	0.50	0.59	0.45	-0.29	0.05	0.02	0.59	0.60	0.55	0.78	0.77	0.67
	AT-0029	0.68	0.66	0.61	0.59	0.57	0.49	-0.07	0.18	0.20	0.63	0.56	0.50	0.77	0.78	0.73
	AT-0030	0.77	0.73	0.61	0.61	0.47	0.29	-0.11	0.10	0.23	0.57	0.56	0.45	0.80	0.77	0.71
	AT-0040	0.78	0.78	0.69	0.61	0.60	0.49	-0.12	-0.08	-0.13	0.77	0.77	0.73	0.82	0.80	0.75
	AT-0046	0.69	0.72	0.65	0.52	0.53	0.41	-0.03	0.03	-0.07	0.71	0.70	0.67	0.73	0.74	0.68
	AT-0063	0.74	0.72	0.54	0.68	0.61	0.42	0.01	-0.07	-0.19	0.67	0.65	0.60	0.82	0.79	0.69
	Median	0.70	0.68	0.54	0.54	0.49	0.31	-0.07	0.04	0.06	0.58	0.56	0.50	0.77	0.75	0.68
nival	AT-0005	0.80	0.86	0.53	0.70	0.72	0.19	-0.07	-0.01	0.32	0.67	0.69	0.38	0.84	0.86	0.66
	AT-0009	0.66	0.71	0.58	0.62	0.52	0.27	-0.13	0.14	0.05	0.62	0.52	0.37	0.80	0.76	0.60
	AT-0010	0.71	0.73	0.47	0.48	0.47	-0.18	0.08	-0.04	0.18	0.70	0.68	0.49	0.81	0.78	0.66
	AT-0011	0.82	0.85	0.79	0.73	0.74	0.60	0.03	0.03	-0.02	0.71	0.73	0.65	0.85	0.87	0.79
	AT-0012	0.80	0.79	0.47	0.69	0.68	-0.19	0.02	0.03	0.14	0.76	0.76	0.52	0.88	0.88	0.52
	AT-0013	0.85	0.83	0.74	0.77	0.70	0.46	0.11	0.09	0.17	0.82	0.80	0.72	0.91	0.87	0.80
	AT-0014	0.77	0.75	0.75	0.73	0.66	0.65	0.03	0.03	-0.02	0.74	0.70	0.70	0.85	0.81	0.81
	AT-0024	0.91	0.91	0.91	0.86	0.86	0.84	0.02	0.02	0.04	0.83	0.83	0.81	0.93	0.93	0.92
	AT-0025	0.49	0.83	0.74	0.11	0.68	0.53	-0.41	-0.09	-0.17	0.59	0.77	0.73	0.85	0.85	0.81
	AT-0035	0.66	0.67	0.67	0.48	0.44	0.43	0.01	0.06	0.07	0.66	0.65	0.65	0.71	0.70	0.70
	AT-0037	0.82	0.77	0.46	0.83	0.69	0.18	-0.04	0.03	0.09	0.81	0.74	0.54	0.92	0.83	0.52
	AT-0038	0.75	0.77	0.69	0.54	0.57	0.34	0.08	0.07	0.00	0.56	0.58	0.45	0.81	0.82	0.71
	AT-0039	0.58	0.71	0.63	0.49	0.62	0.46	-0.29	-0.03	-0.04	0.68	0.75	0.70	0.85	0.79	0.69
	AT-0043	0.69	0.62	0.59	0.40	0.31	0.34	0.03	0.21	0.02	0.54	0.43	0.41	0.69	0.69	0.62
	AT-0055	0.86	0.92	0.67	0.79	0.85	0.47	0.10	0.00	-0.17	0.84	0.86	0.77	0.92	0.92	0.79
	AT-0060	0.83	0.62	0.62	0.79	0.56	0.49	0.04	0.35	0.33	0.70	0.52	0.49	0.89	0.86	0.81
	CH-0005	0.88	0.84	0.49	0.78	0.68	0.01	0.05	0.03	0.31	0.71	0.64	0.32	0.90	0.84	0.61
	Median	0.80	0.77	0.63	0.70	0.68	0.43	0.03	0.03	0.05	0.70	0.70	0.54	0.85	0.84	0.70
	Median all	0.72	0.72	0.63	0.59	0.58	0.44	-0.05	0.01	0.03	0.68	0.69	0.65	0.85	0.85	0.79



Table E2: Performance metrics for the testing period of the global LSTM models using random static features (LSTM-Rand). Results are shown for the three catchment representations, C_E , C_A and C_P , across all springs. Springs are grouped by seasonality cluster, and median values are reported for each cluster as well as across all springs. The best-performing catchment representation for each spring and metric is shown in bold.

	ALPAKAS	KGE			NSE			rBias			VE			r		
	ID	C_E	C_A	C_P	C_E	C_A	C_P	C_E	C_A	C_P	C_E	C_A	C_P	C_E	C_A	C_P
weak seasonality	AT-0015	0.44	0.47	0.58	-1.73	-1.93	-1.74	0.21	0.23	0.23	0.77	0.76	0.76	0.62	0.66	0.70
	AT-0018	0.55	0.56	0.57	0.55	0.58	0.58	-0.17	-0.15	-0.15	0.81	0.82	0.83	0.84	0.84	0.84
	AT-0019	0.59	0.58	0.55	-0.05	-0.10	-0.31	0.10	0.11	0.12	0.85	0.84	0.83	0.61	0.59	0.57
	AT-0020	0.73	0.67	0.69	-0.35	-0.50	-0.41	0.21	0.22	0.21	0.79	0.78	0.79	0.90	0.89	0.90
	AT-0023	0.57	0.59	0.54	0.66	0.68	0.64	-0.04	-0.04	-0.05	0.88	0.89	0.88	0.87	0.88	0.88
	AT-0033	0.41	0.41	0.39	0.42	0.42	0.40	-0.19	-0.17	-0.19	0.74	0.74	0.74	0.75	0.73	0.73
	AT-0041	0.35	0.33	0.30	0.24	0.10	0.11	0.25	0.31	0.29	0.62	0.58	0.58	0.78	0.79	0.75
	AT-0053	0.65	0.70	0.61	0.54	0.65	0.59	-0.10	-0.09	-0.08	0.89	0.90	0.90	0.90	0.93	0.92
	AT-0056	0.51	0.52	0.53	0.11	0.12	0.16	-0.06	-0.06	-0.06	0.92	0.92	0.92	0.73	0.73	0.76
	AT-0058	0.37	0.33	0.32	0.39	0.32	0.39	-0.01	-0.01	-0.02	0.87	0.86	0.87	0.65	0.58	0.70
	AT-0062	0.30	0.35	0.35	-0.05	-0.01	0.13	0.34	0.36	0.30	0.41	0.42	0.47	0.50	0.57	0.59
	CH-0006	0.93	0.93	0.93	0.94	0.94	0.90	-0.01	-0.01	-0.01	0.98	0.98	0.97	0.98	0.97	0.96
	CH-0010	0.52	0.47	0.55	-0.71	-0.85	-0.83	0.21	0.23	0.23	0.76	0.76	0.75	0.79	0.81	0.80
	CH-0016	0.79	0.83	0.81	0.65	0.67	0.69	0.02	0.03	0.03	0.92	0.92	0.92	0.82	0.85	0.85
	DE-0019	0.91	0.88	0.87	0.82	0.73	0.68	0.04	0.07	0.09	0.92	0.90	0.89	0.92	0.91	0.90
	SI-0038	0.87	0.82	0.82	0.86	0.83	0.85	0.09	0.13	0.13	0.86	0.84	0.85	0.95	0.95	0.97
Median		0.56	0.57	0.56	0.40	0.37	0.40	0.03	0.05	0.06	0.85	0.84	0.84	0.81	0.83	0.82
pluvial	CH-0001	0.67	0.65	0.64	0.73	0.69	0.71	-0.19	-0.21	-0.20	0.72	0.70	0.71	0.91	0.89	0.91
	CH-0004	0.81	0.82	0.85	0.89	0.89	0.87	-0.08	-0.07	-0.04	0.78	0.78	0.75	0.95	0.95	0.94
	CH-0008	0.88	0.88	0.89	0.78	0.79	0.79	-0.01	-0.01	-0.01	0.66	0.66	0.68	0.89	0.89	0.90
	CH-0012	0.85	0.88	0.86	0.75	0.76	0.79	-0.07	-0.04	-0.05	0.83	0.83	0.84	0.88	0.88	0.90
	CH-0018	0.76	0.71	0.74	0.88	0.85	0.85	-0.16	-0.19	-0.17	0.78	0.75	0.76	0.97	0.96	0.95
	CH-0026	0.75	0.72	0.74	0.86	0.85	0.85	-0.08	-0.08	-0.05	0.75	0.74	0.74	0.95	0.95	0.94
	DE-0015	0.79	0.77	0.70	0.84	0.83	0.77	-0.18	-0.17	-0.17	0.78	0.79	0.79	0.95	0.95	0.92
	FR-0007	0.89	0.89	0.85	0.92	0.92	0.88	-0.01	0.01	-0.02	0.79	0.79	0.75	0.96	0.96	0.94
	FR-0011	0.89	0.87	0.91	0.93	0.94	0.90	0.10	0.11	0.07	0.78	0.79	0.73	0.97	0.98	0.95
	FR-0013	0.71	0.69	0.76	0.75	0.73	0.77	-0.04	-0.02	0.02	0.59	0.56	0.57	0.88	0.86	0.88
	FR-0024	0.63	0.57	0.49	0.51	0.39	0.17	0.30	0.36	0.34	0.68	0.61	0.57	0.90	0.90	0.84
	FR-0034	0.48	0.50	0.47	0.68	0.70	0.68	-0.33	-0.31	-0.32	0.60	0.61	0.59	0.93	0.93	0.92
	SI-0012	0.65	0.60	0.68	0.65	0.61	0.59	-0.08	-0.07	0.10	0.46	0.42	0.35	0.82	0.79	0.77
	SI-0016	0.76	0.75	0.78	0.82	0.82	0.82	-0.06	-0.06	0.00	0.69	0.68	0.68	0.92	0.92	0.92
	SI-0035	0.83	0.83	0.81	0.83	0.81	0.78	0.05	0.05	0.16	0.73	0.72	0.69	0.91	0.90	0.90
	SI-0042	0.86	0.85	0.86	0.82	0.82	0.83	0.11	0.13	0.12	0.70	0.69	0.70	0.91	0.92	0.92
Median		0.77	0.76	0.77	0.82	0.81	0.79	-0.06	-0.05	-0.02	0.73	0.71	0.71	0.92	0.92	0.92



nivo-pluvial	AT-0001	0.68	0.66	0.67	0.61	0.61	0.59	0.05	0.01	0.02	0.51	0.52	0.50	0.78	0.78	0.77
	AT-0004	0.18	0.19	0.21	0.27	0.27	0.28	-0.38	-0.38	-0.39	0.26	0.27	0.27	0.57	0.57	0.58
	AT-0006	0.74	0.73	0.72	0.69	0.68	0.64	-0.02	-0.03	-0.04	0.67	0.66	0.64	0.83	0.82	0.80
	AT-0007	0.75	0.74	0.72	0.69	0.67	0.65	0.16	0.17	0.16	0.61	0.60	0.57	0.84	0.83	0.82
	AT-0008	0.55	0.58	0.53	0.54	0.55	0.52	-0.28	-0.26	-0.31	0.58	0.58	0.56	0.77	0.78	0.77
	AT-0021	0.76	0.74	0.75	0.63	0.63	0.65	0.15	0.17	0.14	0.73	0.73	0.74	0.83	0.84	0.84
	AT-0022	0.72	0.69	0.69	0.64	0.64	0.61	0.19	0.21	0.23	0.60	0.59	0.57	0.83	0.83	0.82
	AT-0026	0.61	0.61	0.61	0.73	0.73	0.73	-0.21	-0.20	-0.20	0.71	0.70	0.71	0.93	0.92	0.92
	AT-0027	0.62	0.62	0.59	0.68	0.69	0.64	-0.11	-0.11	-0.11	0.69	0.70	0.67	0.86	0.87	0.83
	AT-0029	0.57	0.60	0.56	0.61	0.61	0.59	-0.06	-0.04	-0.06	0.66	0.67	0.65	0.80	0.80	0.78
	AT-0030	0.77	0.80	0.75	0.71	0.70	0.65	-0.03	0.00	-0.04	0.71	0.71	0.67	0.84	0.84	0.81
	AT-0040	0.94	0.95	0.95	0.93	0.93	0.92	-0.04	-0.03	-0.04	0.90	0.90	0.90	0.97	0.97	0.96
	AT-0046	0.69	0.72	0.64	0.78	0.79	0.73	-0.04	-0.01	-0.05	0.81	0.81	0.79	0.91	0.90	0.89
	AT-0063	0.73	0.76	0.69	0.86	0.86	0.80	0.05	0.10	0.05	0.76	0.75	0.72	0.95	0.95	0.92
Median		0.70	0.70	0.68	0.68	0.67	0.65	-0.04	-0.02	-0.04	0.68	0.68	0.66	0.84	0.84	0.82
nival	AT-0005	0.85	0.84	0.76	0.82	0.81	0.79	-0.02	-0.02	-0.08	0.80	0.79	0.77	0.90	0.90	0.90
	AT-0009	0.67	0.69	0.66	0.65	0.66	0.65	-0.04	-0.03	-0.04	0.68	0.68	0.67	0.81	0.81	0.81
	AT-0010	0.77	0.78	0.88	0.67	0.65	0.75	0.04	0.05	0.00	0.75	0.75	0.79	0.87	0.87	0.88
	AT-0011	0.86	0.85	0.79	0.82	0.82	0.83	0.02	0.03	-0.03	0.78	0.78	0.79	0.90	0.91	0.92
	AT-0012	0.89	0.89	0.82	0.83	0.84	0.80	-0.02	0.00	-0.01	0.82	0.82	0.80	0.91	0.92	0.90
	AT-0013	0.87	0.88	0.90	0.85	0.86	0.87	0.07	0.09	0.09	0.86	0.86	0.87	0.94	0.95	0.95
	AT-0014	0.86	0.85	0.86	0.90	0.89	0.90	0.02	0.02	0.01	0.84	0.84	0.85	0.95	0.95	0.95
	AT-0024	0.86	0.84	0.83	0.88	0.84	0.84	-0.05	-0.04	-0.05	0.86	0.84	0.84	0.94	0.92	0.93
	AT-0025	0.81	0.74	0.77	0.72	0.64	0.68	-0.01	0.00	0.01	0.81	0.79	0.81	0.85	0.80	0.82
	AT-0035	0.81	0.79	0.76	0.66	0.66	0.67	-0.05	-0.02	-0.04	0.74	0.74	0.74	0.82	0.82	0.82
	AT-0037	0.82	0.81	0.85	0.88	0.83	0.88	-0.02	0.00	0.02	0.84	0.82	0.83	0.94	0.92	0.94
	AT-0038	0.76	0.76	0.73	0.70	0.71	0.71	0.02	0.01	-0.03	0.64	0.64	0.64	0.84	0.84	0.84
	AT-0039	0.77	0.77	0.72	0.82	0.82	0.82	-0.01	-0.01	-0.04	0.85	0.85	0.86	0.92	0.92	0.93
	AT-0043	0.88	0.85	0.82	0.84	0.82	0.80	0.04	0.13	0.02	0.77	0.73	0.72	0.92	0.91	0.89
	AT-0055	0.90	0.88	0.90	0.91	0.90	0.89	0.06	0.08	0.08	0.89	0.89	0.88	0.97	0.97	0.96
	AT-0060	0.66	0.64	0.73	0.61	0.58	0.73	0.30	0.31	0.25	0.60	0.59	0.65	0.87	0.86	0.90
	CH-0005	0.87	0.81	0.78	0.89	0.85	0.83	0.01	-0.02	-0.04	0.79	0.76	0.75	0.94	0.93	0.92
Median		0.85	0.81	0.79	0.82	0.82	0.80	0.01	0.00	-0.01	0.80	0.79	0.79	0.91	0.91	0.90
Median all		0.76	0.74	0.73	0.72	0.70	0.71	-0.01	-0.01	-0.01	0.77	0.75	0.75	0.90	0.89	0.90



Table E3: Performance metrics for the testing period of the global LSTM models using environmental static features (LSTM-Env). Results are shown for the three catchment representations, C_E , C_A and C_P , across all springs. Springs are grouped by seasonality cluster, and median values are reported for each cluster as well as across all springs. The best-performing catchment representation for each spring and metric is shown in bold.

	ALPAKAS ID	KGE			NSE			rBias			VE			r		
		C_E	C_A	C_P	C_E	C_A	C_P	C_E	C_A	C_P	C_E	C_A	C_P	C_E	C_A	C_P
weak seasonality	AT-0015	0.42	0.41	0.56	-1.91	-1.86	-1.83	0.22	0.21	0.24	0.77	0.77	0.76	0.64	0.64	0.72
	AT-0018	0.55	0.55	0.53	0.56	0.55	0.54	-0.15	-0.16	-0.16	0.82	0.82	0.82	0.83	0.83	0.82
	AT-0019	0.59	0.58	0.55	-0.13	-0.27	-0.37	0.10	0.12	0.12	0.84	0.83	0.83	0.60	0.61	0.57
	AT-0020	0.70	0.70	0.67	-0.54	-0.42	-0.56	0.22	0.21	0.22	0.78	0.79	0.78	0.86	0.89	0.89
	AT-0023	0.54	0.56	0.56	0.64	0.66	0.64	-0.04	-0.04	-0.03	0.88	0.88	0.88	0.86	0.88	0.85
	AT-0033	0.44	0.43	0.39	0.49	0.47	0.34	-0.12	-0.12	-0.12	0.77	0.77	0.72	0.76	0.75	0.62
	AT-0041	0.34	0.34	0.25	0.21	0.13	-0.13	0.26	0.29	0.36	0.61	0.59	0.53	0.78	0.75	0.67
	AT-0053	0.62	0.63	0.62	0.50	0.57	0.52	-0.10	-0.09	-0.10	0.89	0.89	0.89	0.89	0.91	0.91
	AT-0056	0.51	0.54	0.51	0.12	0.01	0.13	-0.06	-0.06	-0.06	0.92	0.92	0.92	0.75	0.70	0.76
	AT-0058	0.30	0.28	0.36	0.34	0.33	0.36	-0.01	-0.02	0.01	0.86	0.86	0.86	0.63	0.64	0.61
	AT-0062	0.28	0.34	0.39	-0.02	0.05	0.07	0.31	0.33	0.34	0.42	0.43	0.44	0.49	0.56	0.61
	CH-0006	0.92	0.94	0.92	0.93	0.93	0.91	-0.01	-0.01	-0.01	0.98	0.98	0.97	0.98	0.97	0.96
	CH-0010	0.39	0.51	0.41	-1.12	-0.68	-1.18	0.24	0.22	0.25	0.74	0.77	0.74	0.80	0.82	0.79
	CH-0016	0.83	0.83	0.84	0.68	0.70	0.65	0.03	0.03	0.04	0.92	0.92	0.91	0.85	0.86	0.85
	DE-0019	0.90	0.91	0.88	0.79	0.82	0.75	0.03	0.03	0.07	0.92	0.92	0.90	0.90	0.92	0.91
	SI-0038	0.85	0.83	0.78	0.84	0.84	0.82	0.11	0.13	0.15	0.85	0.84	0.83	0.95	0.96	0.96
Median		0.55	0.56	0.55	0.41	0.40	0.35	0.03	0.03	0.05	0.85	0.84	0.83	0.81	0.82	0.81
pluvial	CH-0001	0.72	0.65	0.66	0.77	0.67	0.75	-0.15	-0.22	-0.18	0.74	0.70	0.73	0.91	0.88	0.92
	CH-0004	0.85	0.84	0.84	0.89	0.89	0.87	-0.05	-0.06	-0.03	0.78	0.78	0.75	0.95	0.95	0.94
	CH-0008	0.87	0.87	0.89	0.76	0.75	0.79	0.05	0.03	0.03	0.63	0.63	0.67	0.88	0.88	0.90
	CH-0012	0.86	0.85	0.86	0.73	0.75	0.73	-0.06	-0.06	-0.04	0.83	0.83	0.83	0.87	0.88	0.87
	CH-0018	0.76	0.69	0.72	0.88	0.82	0.84	-0.16	-0.22	-0.17	0.78	0.73	0.74	0.97	0.96	0.95
	CH-0026	0.73	0.74	0.70	0.82	0.83	0.80	-0.08	-0.06	-0.06	0.75	0.75	0.71	0.93	0.93	0.92
	DE-0015	0.81	0.75	0.72	0.85	0.81	0.74	-0.17	-0.20	-0.18	0.78	0.77	0.78	0.95	0.95	0.90
	FR-0007	0.91	0.90	0.85	0.92	0.91	0.88	0.00	0.00	-0.01	0.79	0.78	0.75	0.96	0.96	0.94
	FR-0011	0.89	0.86	0.91	0.94	0.93	0.91	0.10	0.12	0.07	0.79	0.77	0.73	0.97	0.97	0.95
	FR-0013	0.73	0.70	0.76	0.75	0.73	0.77	-0.01	-0.04	0.01	0.58	0.58	0.58	0.87	0.87	0.88
	FR-0024	0.60	0.59	0.42	0.53	0.42	0.04	0.30	0.31	0.37	0.69	0.65	0.55	0.93	0.88	0.84
	FR-0034	0.53	0.55	0.47	0.72	0.75	0.69	-0.28	-0.30	-0.32	0.62	0.64	0.61	0.93	0.94	0.94
	SI-0012	0.66	0.60	0.66	0.64	0.60	0.62	-0.05	-0.11	-0.01	0.43	0.39	0.41	0.81	0.78	0.79
	SI-0016	0.75	0.74	0.76	0.81	0.81	0.80	-0.07	-0.07	-0.01	0.68	0.68	0.65	0.91	0.92	0.91
	SI-0035	0.70	0.85	0.80	0.76	0.80	0.78	0.20	0.05	0.16	0.62	0.71	0.68	0.90	0.90	0.90
	SI-0042	0.84	0.85	0.86	0.82	0.83	0.83	0.12	0.11	0.09	0.69	0.70	0.72	0.91	0.92	0.92
Median		0.75	0.75	0.76	0.79	0.80	0.79	-0.05	-0.06	-0.01	0.71	0.71	0.71	0.92	0.92	0.91



nivo-pluvial	AT-0001	0.69	0.68	0.68	0.64	0.61	0.59	0.05	0.01	0.03	0.53	0.52	0.49	0.80	0.78	0.77
	AT-0004	0.25	0.25	0.24	0.31	0.30	0.28	-0.34	-0.35	-0.34	0.28	0.30	0.27	0.60	0.58	0.57
	AT-0006	0.75	0.71	0.72	0.69	0.67	0.63	0.01	-0.04	-0.03	0.66	0.65	0.62	0.83	0.82	0.80
	AT-0007	0.73	0.74	0.71	0.67	0.68	0.62	0.21	0.18	0.20	0.59	0.59	0.55	0.84	0.84	0.81
	AT-0008	0.59	0.58	0.55	0.57	0.56	0.53	-0.25	-0.27	-0.30	0.59	0.58	0.55	0.79	0.79	0.77
	AT-0021	0.76	0.77	0.75	0.60	0.63	0.63	0.17	0.16	0.17	0.72	0.74	0.73	0.83	0.84	0.84
	AT-0022	0.70	0.71	0.70	0.60	0.63	0.60	0.24	0.20	0.21	0.57	0.60	0.57	0.82	0.82	0.81
	AT-0026	0.59	0.62	0.59	0.72	0.73	0.72	-0.20	-0.19	-0.19	0.70	0.70	0.69	0.93	0.92	0.92
	AT-0027	0.60	0.60	0.49	0.68	0.67	0.56	-0.09	-0.11	-0.11	0.69	0.69	0.62	0.86	0.85	0.80
	AT-0029	0.58	0.54	0.55	0.61	0.58	0.58	-0.01	-0.01	-0.04	0.65	0.63	0.64	0.80	0.79	0.79
	AT-0030	0.83	0.80	0.75	0.68	0.68	0.62	-0.01	-0.04	-0.10	0.68	0.69	0.64	0.83	0.83	0.80
	AT-0040	0.94	0.95	0.94	0.92	0.92	0.91	-0.02	-0.03	-0.02	0.90	0.90	0.90	0.96	0.96	0.96
	AT-0046	0.69	0.67	0.65	0.76	0.76	0.73	-0.01	-0.01	-0.04	0.79	0.79	0.79	0.89	0.89	0.88
	AT-0063	0.73	0.72	0.72	0.85	0.85	0.81	0.05	0.04	0.05	0.76	0.77	0.75	0.94	0.95	0.92
Median		0.69	0.70	0.69	0.67	0.67	0.62	-0.01	-0.02	-0.03	0.67	0.67	0.63	0.83	0.83	0.81
nival	AT-0005	0.84	0.83	0.76	0.81	0.82	0.80	-0.02	-0.03	-0.05	0.79	0.80	0.76	0.90	0.91	0.90
	AT-0009	0.71	0.68	0.71	0.65	0.65	0.66	0.00	-0.02	-0.01	0.67	0.67	0.66	0.81	0.81	0.81
	AT-0010	0.77	0.81	0.84	0.65	0.67	0.73	0.05	0.03	0.01	0.76	0.76	0.78	0.87	0.87	0.88
	AT-0011	0.87	0.86	0.80	0.79	0.82	0.83	0.03	0.02	-0.03	0.75	0.78	0.77	0.89	0.91	0.92
	AT-0012	0.85	0.80	0.71	0.70	0.69	0.67	0.02	0.01	0.01	0.75	0.75	0.74	0.85	0.83	0.82
	AT-0013	0.85	0.85	0.86	0.81	0.82	0.82	0.09	0.08	0.10	0.85	0.85	0.85	0.93	0.94	0.94
	AT-0014	0.87	0.84	0.89	0.88	0.89	0.90	0.04	0.02	0.02	0.83	0.84	0.85	0.94	0.95	0.95
	AT-0024	0.83	0.75	0.79	0.86	0.81	0.80	-0.03	-0.07	-0.04	0.85	0.82	0.81	0.93	0.92	0.90
	AT-0025	0.77	0.72	0.76	0.68	0.63	0.56	0.01	-0.02	0.04	0.80	0.79	0.77	0.82	0.80	0.77
	AT-0035	0.80	0.78	0.79	0.64	0.63	0.67	-0.01	-0.05	-0.03	0.73	0.74	0.74	0.81	0.81	0.82
	AT-0037	0.85	0.81	0.84	0.89	0.87	0.86	0.00	-0.01	0.01	0.84	0.83	0.83	0.95	0.94	0.93
	AT-0038	0.74	0.75	0.70	0.68	0.69	0.66	0.03	0.04	0.00	0.61	0.61	0.59	0.83	0.83	0.81
	AT-0039	0.78	0.76	0.73	0.81	0.83	0.81	-0.01	-0.02	-0.03	0.84	0.86	0.85	0.91	0.93	0.92
	AT-0043	0.87	0.88	0.87	0.78	0.80	0.79	0.07	0.07	0.03	0.70	0.72	0.72	0.89	0.90	0.89
	AT-0055	0.89	0.89	0.89	0.89	0.90	0.90	0.09	0.06	0.07	0.88	0.89	0.88	0.96	0.96	0.96
	AT-0060	0.70	0.68	0.71	0.71	0.68	0.64	0.28	0.29	0.25	0.63	0.63	0.60	0.90	0.89	0.86
	CH-0005	0.86	0.83	0.76	0.87	0.87	0.83	-0.01	-0.01	-0.05	0.78	0.78	0.75	0.94	0.94	0.92
Median		0.84	0.81	0.79	0.79	0.81	0.80	0.02	0.01	0.01	0.78	0.78	0.77	0.90	0.91	0.90
Median all		0.74	0.74	0.72	0.71	0.69	0.69	0.00	-0.01	-0.01	0.76	0.77	0.74	0.88	0.88	0.88



E2 KarstMod: Calibrated snow-routine parameters across catchment representations

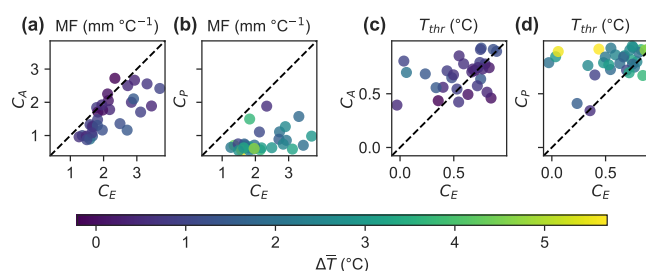


Figure E1. Comparison of calibrated snow routine parameters between catchment representations, based on the median across the 40-model ensemble per spring. Melt factor (MF) for C_A versus C_E (a) and C_P versus C_E (b). Melt temperature (T_{thr}) for C_A versus C_E (c) and C_P versus C_E (d). Each point represents one spring. Point colour indicates the mean temperature difference between the respective catchment representation and C_E ($C_A - C_E$ or $C_P - C_E$).

Author contributions. PT carried out the modelling experiments and data analysis, prepared the figures, and drafted the main part of the manuscript. FJ carried out the aggregation of the meteorological and static input data. Conceptualisation and methodology were developed jointly by PT, TL, FJ, and NG. All authors reviewed and approved the final manuscript.

Competing interests. The authors declare that they have no conflict of interest.

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Global LSTM modelling and model evaluation were conducted in Python. TensorFlow (Abadi et al., 2015) and Keras (Chollet and others, 2015) were used for model implementation and training. Data processing and analysis relied on NumPy (Harris et al., 2020), pandas (The pandas development team, 2020), SciPy (Virtanen et al., 2020), scikit-learn (Pedregosa et al., 2011), and GeoPandas (Van den Bossche et al., 2025). Figures were produced using Matplotlib (Hunter, 2007).

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