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Considering land cover and land use (LCLU) in lumped parameter modeling in forest dominated karst catchments

V. Sivelles¹, H. Jourde¹, D. Bittner^{2,3,5}, B. Richieri², D. Labat⁴, A. Hartmann⁵, G. Chiogna^{2,6}

¹ HSM, Univ Montpellier, CNRS, IRD, Montpellier, France

² Faculty of Civil, Geo and Environmental Engineering, Technical University of Munich, Arcisstr. 21, 80333, Munich, Germany

³ Erftverband, Department for River Basin Management, Am Erftverband 6, 50126 Bergheim, Germany

⁴ Géosciences Environnement Toulouse (GET), CNRS–UPS–IRD–CNES, 14 avenue Edouard Belin, 31400 Toulouse, France;

⁵ Institute of Groundwater Management, Technical University of Dresden, Dresden, Germany

⁶ Institute of Geography, University of Innsbruck, Innrain 52, 6020 Innsbruck, Austria

* corresponding author: vianney.sivelle@umontpellier.fr

Highlights:

- Value of LCLU consideration in lumped parameter modeling of karst spring discharge
- Trade-off assessment between model complexity and performance in karst hydrology
- Considering LCLU have a contradictory influence on hydrological model performance

Abstract:

Lumped parameter modeling approach has been widely applied in karst hydrology for, among other applications, groundwater availability assessment in a context of global change. Nonetheless, such approach generally does not account for land-cover land-use (LCLU) and its impacts on recharge processes. Then, considering a semi-distributed recharge constitutes a relevant approach to capture the impacts of LCLU on flow dynamics but also introduce more complexity in the modeling approach. The present study consists of a multiple hydrological model calibration to assess the implication of considering a semi-distributed recharge in a lumped parameter model and focuses on the uncertainty originating by the model structure. The modeling results are discussed to evaluate the trade-off between hydrological model complexity and hydrological model performance. The study focuses on forest dominated karst areas with three karst catchments: Kerschbaum (Lower Austria), Baget (French Pyrenees) and Oeillal (southern France). Considering a semi-distributed recharge gives better performance for both Kerschbaum and Oeillal catchments hydrological models, while no improvement is obtained for Baget catchment. Systematic consideration of LCLU is thus not necessarily worthwhile in karst environments as it can bring contradictory results in terms of hydrological model performance.

Keywords:

Karst hydrology; Lumped parameter modeling; Land Cover Land Use; Recharge

1 Introduction

One-quarter of the world's population depends on freshwater from karst aquifers (Ford and Williams, 2013). Ensuring a sustainable karst freshwater supply constitutes a major challenge in a context of increasing imbalance between freshwater supply capacity and the needs of a growing population (Stefano et al., 2012; Wada et al., 2016). Moreover, both climate change and anthropogenic pressures, including an increase in water abstraction or changes in land cover and land use (LCLU), may have a strong impact on the future availability of karst water resources (Gleeson et al., 2012; Taylor et al., 2013). A decreasing karst groundwater availability has already been observed in various regions around the world such as in the Mediterranean area (Charlier et al., 2015; Fiorillo and Guadagno, 2012; García-Ruiz et al., 2011; Smiatek et al., 2013), North America (Loáiciga et al., 2000), and Asia (Guo et al., 2005; Hao et al., 2009; Ma et al., 2004; Wu et al., 2017). Moreover, many studies have investigated the potential evolution of karst groundwater resources under various climate change assumptions (Brenner et al., 2018; Chen et al., 2018; Doummar et al., 2018; Nerantzaki et al., 2020) or various future anthropogenic scenarios (Andreas Hartmann et al., 2012; Sivelles et al., 2021). Nonetheless, only a few studies consider the impact of LCLU changes such as urban area expansion or vegetation adaption to climate change in the assessment of global change impacts on karst groundwater (Sarrazin et al., 2018).

Zhao et al. (2020) highlighted on a global scale that vegetation in the karst regions can be more sensitive to changes in precipitation regimes than to temperature. Ellison et al (2012) stated that “forest–water interactions play a crucial role in supplying the atmospheric moisture that becomes precipitation in the hydrologic cycle” and so forest may have a noticeable influence on the rainfall regime on a large scale. Also, forest coverage around the world is in evolution with an estimated loss of around 2.3 million kilometers square and a gain of around 0.8 million kilometers square from 2000 to 2012 (Hansen et al., 2013). Under changing climatic conditions, the vegetation can show an adaption and consequently modify the land-atmosphere exchanges (Bussotti et al., 2014; Klausmeyer and Shaw, 2009; Llorens and Domingo, 2007), which could at the end cause a modification in the recharge processes (Tramblay et al., 2020). Finally, LCLU changes may constitute a first-order factor

in the evolution of groundwater resources, since they may strongly impact the recharge processes. The assessment and prediction of the effects of LCLU changes on groundwater resources require information on the heterogeneities of the recharge processes and thus the implementation of hydrological models that include a distributed or semi-distributed recharge.

One common approach for hydrodynamic modeling in karst systems consists of considering different combinations of the dominant flow components as distinct conceptual buckets (Bittner et al., 2018; Butscher and Huggenberger, 2008; Fleury et al., 2007; Guinot et al., 2015; Mazzilli et al., 2019; Tritz et al., 2011). Such a model can be useful for the long-term assessment of the flow dynamics and groundwater resources evolution. Sivelles et al., (2019) highlighted a decrease of more than 10 % in the water level during spring periods since the 1960s on Aliou and Baget karst systems in the French Pyrenees. Hartmann et al. (2012) show that the discharge could decrease by 30% by the end of the 21st century at the Faria spring in Palestine. Nerantzaki and Nikolaidis (2020) highlighted an increased dryness in terms of frequency, duration and intensity for three Mediterranean karst springs located in Greece. Sivelles et al. (2021) proposed a methodology to assess the relative impact of climate changes and anthropogenic forcing on spring discharge and highlighted climate change as the main factor causing a decrease in the predicted Oeillal's spring discharge, in southern France. In these former studies, the proposed conceptual lumped-parameters models consider homogeneous recharge processes at the catchment scale. Depending on land use, heterogeneities in soil properties, heterogeneities in climate inputs (e.g. convective events, altitudinal gradient), and catchment size, it can be of interest to consider a semi-distributed recharge as shown in former studies (Bittner et al., 2018; A. Hartmann et al., 2012; Ollivier et al., 2020).

The first purpose of this study is to investigate how considering a semi-distributed recharge, depending on LCLU, affects the flow dynamics of a lumped parameter model and more especially the infiltration toward the saturated zone. The second purpose is to identify the appropriate levels of model complexity that allows obtaining the best performance in terms of spring discharge simulations. For that purpose, the study will focus on forest dominated karst areas to avoid bias due to significant differences in terms of the dominant type of LCLU in the recharge area. Therefore, three karst

catchments characterized by recharge areas lower than 50 km² were chosen to run a multi-model calibration considering different levels of complexity in the upper level of the model (i.e. the compartment can be subject to evapotranspiration and so reproduce the land-atmosphere exchanges). Also, the evapotranspiration is supposed independent of the LCLU to avoid uncertainties related to the estimation method as well as the introduction of cultural coefficient. In this way, the study is more related to the impact of model structure rather than input uncertainty.

2 Study sites and data

Figure 1 shows the location and the land-use for the three selected catchments: Kerschbaum (Bittner et al., 2018), Oeillal spring (Sivelle et al., 2021; Sivelle and Jourde, 2020) and Baget (Sivelle et al., 2019). To avoid misinterpretations due to significant differences in terms of dominant land-use, the study focuses on forest dominated karst areas. Table 1 summarizes the main characteristic of the three catchments in terms of climate, geology/lithology and LCLU.

The Kerschbaum spring is located 10 km south of the city of Waidhofen a.d.Ybbs, Lower Austria. Its recharge area covers approximately 2.5 km² and is characterized by a mean annual temperature of 8 °C and annual precipitation of 1405 mm (2001 - 2014). The small-scale recharge area is predominantly covered by beech forests and parts of it by dolomite quarries (Table 1). With a mean annual discharge of 34 l.s⁻¹, the Kerschbaum spring is part of the regional water supply and shows a response time to rainfall events of 1 day (Bittner et al., 2021). The recharge area belongs to the eastern foothills of the Northern Calcareous Alps and consists of a sequence of dolomitic basement rocks, which result in a deep karstified groundwater system. Despite the well-connected network of conduits, the recharge area does not present significant sinkholes and the recharge processes can be assumed to be mainly diffusive (Bittner et al., 2018).

The Oeillal spring is located north of the city of Narbonne (southern France) and drains water from the limestone terrain of the Fonfroide-Monredon massif. The main aquifer in the area runs within the calcareous formation and fed the Oeillal spring, which is located in the Western part of the Narbonne-Sigean sedimentary basin and rises at four spring pools. In the Northern part of the area, there is also an alluvial aquifer which is contained in the Quaternary formation of the Aude river's terrace. The

recharge area covers around 43.2 km² with a potential additional 10 km² contributing zone (Sivelle and Jourde, 2020) and is characterized by a Mediterranean climate with a mean annual temperature of 14.7 °C and annual precipitations of 570 mm (1980-2020). The mean annual discharge is estimated to be around 0.14 m³/s.

The Baget catchment is located 10 km southwest of the city of Saint-Girons (French Pyrenees). Its recharge area covers approximately 13.2 km² and is characterized by a mean annual temperature of 11.8 °C and annual precipitation of 1000 mm (1970 - 2020). The mean annual discharge is estimated to be around 0.45 m³/s. The karstified part of the basin is characterized by metamorphic Jurassic to Cretaceous dolomites, limestones and calcareous marls. These formations deep 70 to 90° southwards, under the slaty Albian-Cenomanian Ballongue flysch that constitutes the southern boundary of the catchment. The contact between karstified formation and non-karstifiable rocks give the west-east direction of the main drainage system. The northern limit of the Baget drainage basin consists of a secondary fault from the North Pyrenean fault, the Alas fault.

Both Kerschbaum and Oeillal catchment are impacted by the presence of quarries and Oeillal catchment is also impacted by the presence of urban areas. The Baget catchment differs from other catchments due to the presence of non-karstic impluvium that represent 20 % of the total recharge area. This part of the watershed consists of the slaty Albian-Cenomanian Ballongue flysch, considered an impervious formation. The orientation of the main drainage system in the area is given by the contact between the Ballongue flysch and the karstified part of the basin in the west-east direction (Debroas, 2009; Sivelle et al., 2020). This part of the watershed contributes to the spring discharge through surface runoff rather than infiltration in the main aquifer.

The three selected catchments are characterized by a small recharge area (< 50 km²) and with a LCLU dominated by forest that represents 96% of the total recharge area for Kerschbaum, 62.7% of the total recharge area for Oeillal and 72% of the total recharge area for Baget (Figure 1). The catchments are chosen based on their dominant LCLU and their comparable size of recharge areas to avoid bias related to LCLU and scale effects. Regarding Kerschbaum and Baget, the two systems show similar catchment size and land cover characteristics but different geological and climate properties. The

Kerschbaum springshed is a dolostone karst system with a mean annual temperature of 8 °C. On the contrary, the geology of Baget is dominated by limestones and the climate is characterized by a mean annual temperature of 12.2 °C. Moreover, the Kerschbaum and Baget springs have a mean discharge of 34 and 450 l.s⁻¹, respectively.

3 Methodology

3.1 Hydrological models

3.1.1 Semi-distributed recharge in lumped parameter modeling

A semi-distributed recharge can be implemented in lumped parameter model at the catchment scale employing two distinct approaches which consist of either increasing the model complexity (and so adding more parameters) or considering distributed meteorological data (precipitation, land-surface temperature, evapotranspiration) as input in the model. Such approaches have proved their efficiency in improving karst aquifers hydrological modeling:

Ollivier et al. (2020) propose the KaRaMel model with several lumped model units running in parallel. The structure of the model is based on a three-compartments model: the upper compartment collects precipitation, hosts evapotranspiration, and governs infiltration toward a slow discharge compartment (M) and a rapid discharge compartment (C). The outlet discharge consists of the sum of discharge from the slow and rapid compartments. Such model structure is widely used in karst hydrology (Baudement et al., 2017; Moussu, 2012; Pinault et al., 2001; Schmidt et al., 2014). The modeling is performed over the Fontaine de Vaucluse aquifer (southern France) showing a large watershed area (about 1600 km²). The model structure allows accounting for both slow matrix flows and fast conduit flows (Fleury et al., 2007; Mazzilli et al., 2019) considering there is no exchange between these two flow components, although exchanges flow can be observed in the non-saturated zone (Dal Soglio et al., 2020). The input data consists of gridded data set with a spatial resolution of several kilometers that cannot be considered as valuable input for hydrological modeling on karst aquifers with recharge areas lower than 50 km². Such an approach allows to better assess the recharge distribution, with heterogeneities due to environmental factors such as geology, LCLU or even meteorological forcing

(precipitation, evapotranspiration). In large karst catchments such as Fontaine de Vaucluse, the recharge distribution explains a large part of the discharge variation at the outlet (Ollivier et al., 2020). Another approach relies on the introduction of hydrotopes, which were considered in the LuKARS model (Bittner et al., 2018). Each hydrotope is characterized by land use and soil type and conceptually represents the vadose zone. The model structure consists of a compartment contributing to the recharge of the saturated zone, including also a loss function flowing to secondary springs and a hysteresis function (Tritz et al., 2011) flowing directly to the spring. In the LuKARS model, each hydrotope is exposed to effective precipitation depending on interception, evapotranspiration and, when applicable, snow processes. The hydrotopes consist of several lumped parameter models running in parallel, in a similar way as the KaRaMel model (Ollivier et al., 2020). Each hydrotope contributes to recharge, loss and fast flow depending on their relative area, their distance from the spring as well as the land use and soil properties. The use of such “hydrotopes” relies on the assumption of a hydrophysical uniqueness of each hydrotope (Bittner et al., 2018).

3.1.2 Model structures

Two lumped parameters models are implemented in this study to account for a different conceptualization of the flow processes. The first model corresponds to the original LuKARS model (Bittner et al., 2018) and the second model corresponds to a coupled model with the concept of hydrotopes implemented in the LuKARS model in the upper level of a model structure with two interconnected compartments in the lower level of the model structure, as proposed in the KarstMod modeling platform (Mazzilli et al., 2019). A detailed description of LuKARS and KarstMod and their underlying equations are provided in appendix A and appendix B, respectively. Figure 2 summarizes the different model structures for each catchment concerning both the upper and lower level of the model structures and a description of the associated parameters is given in Table 2. In this study, the different configurations in the upper level are tested, considering 1 up to 4 hydrotopes, bringing also more uncertain parameters for the model calibration. Conversely, the lower level is chosen for each catchment based on former studies for Oeillal (Sivelle et al., 2021), Kerschbaum (Bittner et al., 2018)

and Baget (Sivelle et al., 2019). The present study focuses on the characterization of the infiltration processes through two fluxes denoted Q_{is} and Q_{hy} that flow from the upper level toward a compartment in the lower level or directly to the spring (Figure 2). In this study, the original “Linear baseflow storage” from Bittner et al, (2018) is referred to as a compartment with linear discharge law for notation consistency with the use of coupled LuKARS and KarstMod model structures. Also, this compartment is denoted M (Figure 2) and represent the baseflow as suggested in the original KarstMod model (Baudement et al., 2017; Mazzilli et al., 2019; Sivelle et al., 2019).

In this study, the lower level in the model structure for Kerschbaum corresponds to a compartment with linear discharge law implemented in the original LuKARS model (Bittner et al., 2018) whereas a model structure considering matrix-conduit exchanges in the lower level is applied within the Baget catchment (Sivelle et al., 2019). Concerning the Oeillal spring, a threshold effect in lower level of the model structure (i.e. compartment with linear discharge law) allows reproducing the change in flow dynamics during the period of low water table elevation (Sivelle et al., 2021).

The upper level of the model structure consists of four lumped model units running in parallel, denoted ‘hydrotopes’, characterized by different land uses and soil types. It conceptually represents the vadose zone compartment (higher level with the continuum soil-epikarst-infiltration zone). A hydrotope is analogous to a bucket that has three discharge components with different flow directions: [1] the quickflow component Q_{hy} ($L^3 T^{-1}$) is characterized with a hysteresis function (Tritz et al., 2011) and is directly transferred to the spring outlet, [2] the secondary spring discharge Q_{sec} ($L^3 T^{-1}$) is transferred out of the system and do not contribute to the spring discharge or the lower compartment recharge and [3] the recharge Q_{is} ($L^3 T^{-1}$) is transferred to the lower compartment.

The lower level of the model structure in the LuKARS model consists of one compartment with linear discharge law. The recharge of the compartment consists of the sum of the intra-storage flow Q_{is} from each hydrotope. The outlet discharge of the lower compartment is transferred to the spring. The total spring discharge consists of the sum of the fluxes flowing from the compartment with linear discharge law Q_{MS} ($L^3 T^{-1}$) and the fluxes from the hydrotopes Q_{hy} ($L^3 T^{-1}$) with a hysteretic behavior.

Concerning the coupled LuKARS-KarstMod model, the lower level of the model structure consists of two interconnected compartments denoted M (representative of slow linear flow dynamics that mainly occurs in the matrix) and C (representative of quick non-linear flow dynamics that may occur in conduits and/or unclogged fractures). Then compartment M corresponds to the capacitive function of the aquifer, whereas compartment C is more related to the transmissive function of the aquifer. Both M and C can be filled with water flow from the upper compartment, which are the intra-storage flow Q_{is} and the quick-flow component Q_{hy} . The flow partition is made through a portioning coefficient for both Q_{is} flowing to M or to C and Q_{hy} flowing to C or to the spring. One should note that the original KarstMod modeling platform also implemented such flow partition from the compartment in the upper level to the different compartment of the lower level. The difference for the coupled LuKARS/KarstMod model relies on the use of several buckets running in parallel rather than a single bucket with different discharge coefficients toward the bucket in the lower level of the model. Such conceptualization brings more complexity to the model structure and increases the number of uncertain parameters for the model calibration.

Finally, the two proposed models (Figure 2) consist of modular “bucket-style” model of lumped parameters that enable to build of interconnected compartments, depending on different levels of complexity in both upper and lower levels of the models. In this study, it should be noticed that hydrotopes can be activated/deactivated depending on the levels of complexity considered in the upper level of the model to run the fluxes contributing either to the recharge of the lower level or directly to the spring discharge. So, the number of hydrotopes varies depending on how the heterogeneity in the upper level is considered. Table 2 summarizes the model structures in terms of flow conceptualization in the upper and lower level of the model for the three catchments

3.1.3 Model calibration

The hydrological models were implemented in the Python environment (Summerfield, 2010) while the parameter estimation was performed using a particle swarm optimization (PSO) procedure (Eberhart and Kennedy, 1995) implemented in the “pyswarm” package (Lee, 2014). This approach leads to the

definition of a unique optimal parameter set for each model configuration and therefore this study does not address parametric uncertainty and model equifinality since the study focuses on the uncertainty originating by the model structure. The data set for the calibration and validation of the hydrological model depends on the available data and the calibration procedure is performed on the same time intervals considered in the former studies to avoid bias due to the calibration period on the parameter estimation (Mazzilli et al., 2012). The calibration is made on a period of 1 year for the Kerschbaum spring, 18 months for the Oeillal spring and 10 years for the Baget. The calibration and validation periods are presented in Table 3. The calibration is made on a period where the required data are available on a daily time step. Regarding the Oeillal spring, validation data consists of sparse temporal discharge time series, measured before installation of probes for continuous hourly measurement (Sivelle and Jourde, 2020). Also, adding BE in a weighted function with KGE was required to give more importance of the water balance in the calibration procedure and to better reproduce the significant flow decrease during the summer period.

3.2 Model evaluation

3.2.1 Model evaluation using performance criteria

The metrics used for hydrologic model calibration and evaluation are mainly based on the comparison between observed and simulated streamflow. According to Hauduc et al. (2015) model errors can be calculated in different ways and expressed as performance criteria, allowing to evaluate model performance numerically. Several studies have proposed number of performance criteria (Bennett et al., 2013; Ferreira et al., 2020; Hauduc et al., 2015; Jackson et al., 2019). To assess different aspects of the model performance, it is recommended to adopt a multi-objective model evaluation with a combination of different performance criteria (Huo and Liu, 2020; Monteil et al., 2020).

In this paper, the hydrological models are evaluated with some performance criteria widely used in karst hydrology: the Nash-Sutcliffe efficiency NSE (Nash and Sutcliffe, 1970), the Kling-Gupta efficiency KGE (Gupta et al., 2009), the non-parametric Kling-Gupta efficiency KGENP (Pool et al., 2018). To evaluate the model performance in terms of volume of transit, the modified balance error

BE (Perrin et al., 2001) and the volumetric error VE (Criss and Winston, 2008) are also considered. The correlation coefficient of Pearson R_p as well as Spearman R_s are also considered. Then, hydrological model evaluation is performed using an ensemble of 7 performance criteria, allowing to account with different aspect of the model performance. For more information, the reader may refer to some literature review (Bennett et al., 2013; Ferreira et al., 2020; Jackson et al., 2019). Given that the model structures are characterized by a different number of parameters, the Akaike Informative Coefficient (AIC) is computed such as $AIC = 2k + N\ln(RSS)$, where k is the number of model parameters, N the number of observations and RSS is the sum of the squared residuals. The AIC penalizes the model structures with large number of parameters and gives information on how the performance may evolve with the number of uncertain parameters.

The various performance criteria are plotted according to a “radar chart”, which consists of a polygon where the position of each point from the center gives the value of the performance criteria. One should note that all the performance criteria used in this study are given with a perfect model fitting when the value is equal to 1. Then, plotting several models in the same radar plot allows a quick comparison of the model performance according to the various criteria.

3.2.2 Model evaluation using time series analysis

In karst hydrology, the auto-correlation function (ACF) is frequently used to characterize the temporal structure of hydrological signals under the linear-stationary hypothesis (Labat et al., 2000a; Larocque et al., 1998; Mangin, 1984; Padilla and Pulido-Bosch, 1995; Panagopoulos and Lambrakis, 2006). Mangin (1984) proposed to determine the memory effect of karst aquifers as the lag time value where the ACF of the spring discharge time series reaches the value of 0.2. This approach is commonly used to characterize hydrodynamics in karst aquifers (Lorette et al., 2018; Sivelles and Jourde, 2020). In addition, the cross-correlation function (CCF) between rainfall and spring discharge provides an approximation of the impulse response (Mangin, 1984) when assuming the rainfall consists of a random process (white noise). Also, it describes the capacity of a system to transform the rainfall into discharge. The higher the CCF peak, the more the system acts as a piston. Moreover, the lag time for

the occurrence of the maximum value in CCF corresponds to the time of response. Due to high heterogeneities in karst aquifers, the response time can be dependent on the seasonal variability in rainfall intensity (Delbart et al., 2014). Both memory effects and response time can be dependent on the sampling frequency of the rainfall-discharge time series (Sivelle and Jourde, 2020) because of the occurrence of several processes with characteristic time covering several orders of magnitudes (Blöschl and Sivapalan, 1995). Lumped parameter modeling can show bias such as underestimation of the memory effect and overestimation of CCF peak (Sivelle, 2019) and may testify the importance of considering low frequencies component in the simulated impulse response since the high frequencies processes appear to be predominant. Such time series analysis can provide information about the hydrological model performance in addition to the performance evaluation through numerical performance criteria such as NSE, KGE or KGENP.

In addition, the wavelet multiresolution analysis (MRA) is applied to project the spring discharge time series on an orthogonal basis of wavelet and scale functions (Labat et al., 2000b; Mallat, 1989). The basis is generated from a filter band following a dyadic scale. The projection allows building for each level of this scale the component of the signal that explains the variability at this scale. The decomposition is orthogonal and therefore the sum of all components (details and residue or smooth) give back the initial signal. For a deeper hydrological model evaluation, Sivelle (2019) runs MRA on both observed and simulated spring discharge time series and calculate the goodness of fit with the NSE criteria for each scale. Application on highly karstified watersheds such as Aliou and Baget karst systems shows the weakness of a daily rainfall-discharge model for the high frequency (scale < 8 days) and for the 8-months scale (scale = 256 days). Such an approach can be useful to evaluate hydrological model performances, in addition to ACF and CCF, since it gives a deeper description of the model bias. Indeed, since the usual performance criteria consider the mean errors it does not capture how the model errors can be structured in time and frequency and so how the model can be biased in forecasting purposes.

4 Results and discussion

4.1 Hydrological models' calibration and validation

The calibrated model parameters set for LuKARS model on Baget, Oeillal and Kerschbaum catchments are reported in Table 4 whereas the performance criteria for both the calibration and the validation periods are shown in Figure 3. The performance criteria are color scaled from red for bad values to blue for good values, where the closer the value to 1 the better the fit between observed and simulated spring discharge. The simulated spring hydrographs are reported in Figure 4 and the radar chart for model performance evaluation are given in Figure 5.

The LuKARS model shows quite satisfactorily performance criteria for both Kerschbaum and Oeillal and provides lower performance criteria on the Baget catchment. In comparison, the coupled LuKARS/KarstMod model provides higher performance criteria values although it appears to be quite close to the performance criteria with the KarstMod model (Sivelle et al., 2019) where $NSE = 0.59$, $BE = 0.94$ and $KGE = 0.61$ within the same calibration period.

The first LuKARS application on the Kerschbaum catchment counts 4 hydrotopes and shows satisfactorily performance criteria (Bittner et al., 2018). Here, the LuKARS model application with a lower number of hydrotopes shows lower performance criteria values but is still quite satisfactorily. Indeed, the LK_01 and LK_04 model structures show tiny close BE and VE values. Conversely, other performance criteria show significant differences when the model structure considers at least two hydrotopes in the upper level. Both LK_03 and LK_04 outperforms with the NSE, KGENP, R_s and R_p and share close performance. Thus, a comparison of the different combinations of hydrotopes may allow assessing the trade-off between model complexity (i.e. number of calibration parameters) and the model performance. Analysis of the simulated spring hydrograph (Figure 4) shows that whatever the number of active hydrotopes, the LuKARS model allows capturing the complete spring hydrograph in a quite satisfactorily way. Moreover, increasing the number of hydrotopes allows to better capture the recession part. Indeed, the LK_01 model structure shows an important misfit during recession periods, with a quite permanent offset (while the recession dynamics appears to well reproduced) and underestimates the flood peaks. LK_02 model structure produces a better fit for the recession periods but overestimates the flood peaks (Figure 4). Finally, LK_03 and LK_04 model structures seem to provide a satisfactorily fit during both flood and recession periods of the spring

hydrograph. All LK model structures show very good BE and VE errors and both LK_03 and LK_04 model structure outperforms other LK model structures considering most of the performance criteria (Figure 5). The AIC shows a lower value when considering the LK_03 model structure within the calibration period compared with the other LK model structures. Then the model performance increase does not compensate for the introduction of additional parameters for Kerschbaum when moving from LK_03 to LK_04. Nonetheless, a higher number of hydrotopes gives higher performance for both the calibration and validation periods (Figure 3). Considering the NSE criteria one should note a significant decrease in the performance criteria between calibration and validation periods, whereas the other criteria show quite satisfactory agreement. It may testify significant errors on flood peaks estimation within the validation period while the model correctly reproduces water balance (VE and BE) and correlation (R_p and R_s).

Concerning the Oeillal spring's catchment, the total landcover consists of four types of land use: (i) quarries covering 2% of the total area, (ii) urban areas covering 4.5% of the total area, (iii) vineyards and agricultural plots covering 30.8% of the total area, and (iv) forests and natural plots covering 62.7% of the total area (Figure 1). The first LuKARS application within the Oeillal spring's catchment consists of two hydrotopes that represent an impervious zone (quarries and urban area) and an infiltration zone (Sivelle et al., 2021). Here, the LK_03 model structure is introduced to consider different LCLU in the infiltration zone with a distinction between wine yard and agricultural plots, covering 30.8% of the total recharge area, and forest, covering 62.7 % of the total recharge area. In a general way, the different LK model structures shows close performance considering KGE, BE, VE and R_p whereas LK_02 model structure outperforms considering the KGENP. Thus, the different LK model structures gives satisfactorily results for the different performance criteria, although some minor changes can be observed within the different LK model structures. Elsewhere, the model structures include a threshold effect in the lower compartment with linear discharge law, where all LK_01, LK_02 and LK_03 model structures show quite similar values for both the height of the threshold M_{min} around 2 to 5 mm and the discharge parameter for the upper fluxes out of the compartment kMS_{top} around 0.008 mm.day⁻¹. Conversely, hydrotope 2 and hydrotope 3 within the

LK_03 model structure shows contrasted discharge coefficient values for the fast flow going directly to the spring, with *hyd2_khy* around 224 m mm⁻¹.day⁻¹ and *hyd3_khy* around 740 m mm⁻¹.day⁻¹. The discharge coefficient for the slow flow going to the lower level of the model structure also shows contrasted values with *hyd2_kis* around 0.29 m mm⁻¹.day⁻¹ and *hyd3_is* around 0.04 m mm⁻¹.day⁻¹. It testifies that the LK model, whatever the number of active hydrotopes, allows to capture the slow recession dynamics of the karst system associated with the Oeillal's spring. Then, considering a different number of hydrotopes only affects the flow dynamics from the upper to the lower level and allow to correctly reproduce the spring hydrographs (Figure 4). The AIC criteria show the lower value for the LK_01 within the calibration period (Figure 3). It may call into question the interest of considering a pseudo-distributed recharge for calibration purpose only. The decrease of the performance criteria within the validation period might be the consequence of the sparse temporal resolution of discharge time series during the validation period (i.e. monthly gauging). Indeed, such discrepancy in performance criteria between periods with continuous monitoring and period with sparse temporal measurement was already experienced in the former study (Sivelle and Jourde, 2020). Nonetheless, the LK_03 model structure shows higher performance criteria within the validation period.

Considering the Baget catchment, Sivelle et al. (2019) proposed a conceptualization of the hydrodynamic behavior based on the KarstMod model (Mazzilli et al., 2019) without any consideration for LCLU and so considers a homogeneous recharge at the catchment scale. To assess the impact of considering a semi-distributed recharge in the model structure, the original compartment E is replaced by the LuKARS model conceptualization with 4 hydrotopes within the upper level of the model structure. The model then corresponds to the coupled LuKARS and KarstMod model (Figure 2), denoted LK-KM. As a comparison, the classical LuKARS model, denoted LK, is also calibrated considering 1 up to 4 hydrotopes. The LK_01 and LK_02 model structures show poor performance criteria regarding the NSE and KGE both lower than 0.5 which is also significantly lower than the performance observed with the original KarstMod model where NSE = 0.59 and KGE = 0.61 (Sivelle

et al., 2019). The LK_03 and LK_04 model structures show performance criteria closer to the original KarstMod model although the value for both NSE and KGE is still lower.

Analyses of the simulated spring hydrograph together with the observed one (Figure 4) show that increasing the number of hydrotopes leads to dramatically underestimating the discharge peaks, whereas all the LK model structures, with 1 up to 4 hydrotopes, provides quite comparable flow dynamics during recession periods. In a general way, one should note a spring discharge overestimation during significant recession periods such as July to September 1971, with both LK and LK-KM models. Also, the LK-KM model simulates higher discharges during floods, which is following the model structure that includes a compartment with nonlinear discharge law in the lower level of the model structure contrary to the LK model structures that consider one compartment with linear discharge law. Considering the LK_03 model structure, *hyd3_kis* is around 1 mm.day⁻¹ whereas concerning LK_04 model structure both *hyd3_kis* and *hyd4_kis* are also around 1 mm.day⁻¹. Then, the introduction of a fourth hydrotopes (when moving from LK_03 to LK_04 model structure) does not allow to differentiate the dynamics for the intra-storage fluxes from the upper level to the lower level. Moreover, *hyd2_kis* is still in the same range of values when moving from LK_03 to LK_04 model structures with a value around 7.6 mm.day⁻¹ and 7.2 mm.day⁻¹ respectively. It might show that the recharge dynamic from hydrotope 2, corresponding to poor vegetation cover, is well contrasted with the hydrotopes 3 and 4 corresponding to agricultural plots and forests respectively. Conversely, hydrotopes 3 and 4 cannot be separated in terms of recharge dynamics and brings back into question the assumption of hydrophysical uniqueness as well as the need of considering an additional hydrotope in the model structure. Finally, both LK and LK-KM models within the Baget catchment provide contradictory results with the above application within the Kerschbaum and the Oeillal spring catchments. Indeed, a higher number of hydrotopes do not necessarily provide a better model performance criterion (Figure 3 and Figure 5). Also, the AIC criteria confirms such analysis since the lower value concerns the model structure with 1 hydrotope for LK model and with 2 hydrotopes for LK-KM model and so the gain in model performance does not compensate for the penalization due to the introduction of additional parameters. Also, such observations within the calibration periods are

consistent with the performance criteria calculated within the validation periods for which the lowest AIC values are obtained for LK with 1 hydrotope and LK-KM with 2 hydrotopes, as observed within the calibration period.

4.2 Model evaluation using time series analysis

4.2.1 Autocorrelation and crosscorrelation function analysis

The ACF is calculated on both observed and simulated spring discharges within the different model structures for the three karst catchments (Figure 6). The ACF calculated on observed and simulated spring discharges for the Oeillal spring with the LK model structures look very closely. The memory effect appears to be well estimated at around 80 to 90 days. Conversely, the ACF calculated on simulated discharge for Kerschbaum seems to systematically underestimate the memory effect of 40 days. The second peak for a lag value around 65 days appears to be reproduced by the LK models, although the peak appears less frankly with the LK_01 model structure. Concerning the Baget catchment, the LK models generally estimate very poorly the memory effect of 17 days. Indeed, LK_01 and LK_02 model structures provide a lower value around 9 days whereas LK_03 and LK_04 model structures overestimate the memory effect, all the more with the LK_04 model structure that gives a memory effect of around 45 days. The LK-KM models provide an underestimation of the memory effect although the higher the number of hydrotopes the closer the ACF on simulated discharge to ACF on observed discharge. One should note that such misfit considering the ACF was already investigated within the Baget catchment considering daily rainfall-discharge lumped parameter modeling (Sivelle, 2019) due to a short response time that may require a higher sampling frequency (Labat et al., 2000a).

In the same way, CCF is calculated between rainfall and both observed and simulated spring discharge within the different model structures for the three karst catchments (Figure 7). Concerning the Oeillal spring, CCF based on observed and simulated discharge appears very close when considering LK_03 model structure. Then, the impulse response of the karst system with a slow recession dynamic appears well reproduced with both the LK_02 and LK_03 model structures whereas the LK_01 model

structure fails to reproduce the quick time of response. Concerning Kerschbaum, the LK_02 model structure seems to overestimate the CCF peak amplitude and to under estimate the persistence of correlation for lag values larger than 10 days. Also, the second peak around 65 days is well reproduced although the LK_01 model structure gives a lower CCF peak amplitude. Such a second peak in the rainfall-discharge CCF can be the consequence of the existence of the slow flow dynamics, which may have a delayed contribution with an important response time. Such observation can be consistent with the lithology of the Kerschbaum catchment dominated by dolostones, and a low value of the discharge coefficient for the compartment with linear law with an order of magnitude of 10^{-4} m.day⁻¹. This value is in contrast with values around 10^{-2} m.day⁻¹ for both Baget and Oeillal, dominated by limestones. Then the LK models allow capturing both short-term and mid-term responses although the short-term response with LK_04 model structure appears delayed. Within the Baget catchment, both LK and LK-KM models seem to overestimate the CCF peak value although the LK_04 and LK_04-KM model structure show lower peak value of the CCF and so closer to the CCF based on observed data. Such overestimation of the CCF peak was already observed with the KarstMod model (Sivelle, 2019).

4.2.2 Orthogonal wavelet decomposition

Application of orthogonal wavelet decomposition on both observed and simulated spring discharges allows to calculate the performance criteria according to a dyadic scale (Figure 8) and to evaluate the model performance across different temporal scales. Here, the performance criteria consist of the bounded version of the NSE criteria (Mathevet et al., 2006), denoted NSE_c2m. It allows to reduce the amplitude of variation between -1 and 1. One should note that, the bounded version of NSE criteria keeps the same meaning with a comparison of the model errors with a “naïve” predictor (i.e. the mean of the observed spring discharge time series) where positive values mean the model is a better predictor and a NSE_c2m value of 1 corresponds to a perfect fit between the model prediction and the observation.

Figure 9 shows the performance criteria (i.e. the bounded version of NSE) as a function of the scale. Concerning the Kerschbaum catchment, both LK_03 and LK_04 seems to outperforms for the

various scales, excepted for the 16 days scale, where all the LK model structures gives lower NSE_{c2m} values. Considering the periods larger than 32 days the LK₀₂, LK₀₃ and LK₀₄ models shows close performance, larger than the LK₀₁ model structure. Concerning the Oeillal spring, LK₀₂ and LK₀₃ model structures outperform the LK₀₁ model structure for the scales from 2 days to 128 days whereas as considering the larger periods all LK model structures show quite close performance. Also, all the LK model structures show poor performance criteria for the high frequency (periods lower than 8 days) whereas the low frequencies (period larger than 64 days) give much higher NSE_{c2m} values. Due to the slow recession dynamics of the Oeillal spring system, and the important contribution of the lower compartments in the spring discharge, it is difficult to well capture the fast flow dynamics. This is also observed with the rainfall-discharge CCF that shows a low peak value and testify of an important smoothing effect operated by the karst system. Such results may testify to the importance of considering several flow dynamics from the non-saturated zone to the capacitive function of the aquifer. Then, since most of the effective rainfall flows toward the lower level of the model structure (Figure 2) a suitable characterization of the recharge toward the capacitive function of the aquifer may constitute an important step for the assessment of groundwater resource variability.

Concerning the Baget system, all the LK model structures present close performance criteria for the temporal scale above 128 days whereas the performance for the smaller scale can show a significant difference. This may indicate that for a reactive karst system such as Baget, the high-frequency processes can be better reproduced by considering homogeneous recharge at the catchment scale. Indeed, increasing the number of hydrotopes seems to degrade the performance criteria for periods lower than 100 days. This is observed when the lower level is supposed to be a compartment with linear discharge law, and so the saturated zone consists of a unique flow dynamic. Over the Baget area, former studies have shown the existence of a well-developed drainage system (Mangin, 1975; Marsaud, 1996), with efficient quick flow evidenced by artificial tracer tests (Labat and Mangin, 2015; Sivelles and Labat, 2019) and highlighted the interest of considering two flow dynamics with exchange flow (Sivelles et al., 2019). Then, considering a lower level of the model structure with a more complex structure highlight that whatever the number of hydrotopes the model performance is comparable,

scale by scale. In the end, increasing the number of hydrotopes does not bring better performance either in the high frequency or the low frequencies.

4.1 Effect of hydrotopes on hydrodynamics

To quantify the impact of considering a different number of hydrotopes on the flow dynamics, the monthly mean intra-storage flow Q_{is} (discharge from the hydrotopes in the upper level to the lower level of the model structure, considered as a proxy of the recharge) is calculated within the month of the year (Figure 10). It gives an overview of how the recharge may occur along with the hydrologic cycle. Due to the bad performance of the modeling approach within the Baget karst system, the analysis is made only within the Kerschbaum spring and the Oeillal's spring, where considering several hydrotopes helped improving the hydrological model performance. To perform a preliminary assessment of the influence of parametric uncertainties, the estimation of the mean Q_{is} is made on the 0.99 percentile ensemble of simulated hydrographs using the Latin Hypercube Sampling (LHS) procedure implemented in the SAFE toolbox (Pianosi et al., 2015). Then, the simulation with the highest objective function is reported in solid line, while the confidence interval is given through a colored envelope (Figure 10). The simulated spring hydrograph is given within the calibration period while the recharge is estimated on periods of 10 years, considering the hydrological model can be used out of calibration periods due to acceptable performance within the validation period (Figure 3). The estimation is made on the 2010-2020 periods for Oeillal and 2006-2016 periods for Kerschbaum.

Kerschbaum and Oeillal's spring catchments show very different pattern in the proxy of recharge along the hydrological cycle. Indeed, Q_{is} appears quite constant along with the month of the year on Kerschbaum while Q_{is} shows significant temporal variation with period of important recharge during spring and autumn, and low recharge during the summer period. Such discrepancy is a consequence of the exposition to different climate which is warm-moderate regional climate for Kerschbaum against Mediterranean climate for the Oeillal's spring catchment. Within the Oeillal's spring the regime of recharge follow the main Mediterranean precipitation pattern with two rainy seasons, in spring and autumn periods.

The analyse show that for both Kerschbaum and Oeillal's spring catchment the confidence interval on the variation of Q_{is} along with the month of the year appears to reduce when considering a higher number of hydrotope. Such results are consistent with the analysis of the estimated parameters (Table 4). Indeed, for both Kerschbaum and Oeillal's spring catchment, the parameter values related to the lower compartment appears well constrained, whatever the number of hydrotopes in the upper part of the model structure. Then, considering infiltration heterogeneities through a semi-distributed model seems to better capture the infiltration processes from the upper level to the lower level compartments on both Kerschbaum and Oeillal's spring karst systems.

5 Conclusion

This study investigated how considering LCLU, and thus a semi-distributed recharge impacts the performance of a lumped parameter hydrological model as well as the recharge dynamics in forest dominated karst system. The model performances are compared using numerical performance criteria, time series analysis (i.e. auto-correlation analysis, cross-correlation analysis and wavelet multiresolution analysis) and analysis of the simulated recharge dynamics. Considering a semi-distributed recharge gives better performance for both Kerschbaum and Oeillal catchments hydrological models, while no improvement is obtained for Baget catchment. Kerschbaum and Oeillal karst springs are characterized by slower recession dynamics than the Baget spring. The results within the Baget catchment show that considering a more complex conceptualization of recharge processes does not bring better hydrological model performance. The Baget is characterized by a high degree of karstification, an important spring discharge variability as well as an important role of matrix-conduit exchanges. The heterogeneities in recharge processes are difficult to capture considering a daily lumped parameter hydrological model. A deeper investigation considering a higher frequency base might be needed to better assess the impact of LCLU on recharge processes. Also, considering a semi-distributed recharge seems to reduce the uncertainty in the quantification of the internal fluxes, flowing from the upper level to the lower level of the model structure. The main results of the study consist of a first step in the assessment of the trade-off between hydrological model complexity and hydrological model performance, in a framework of lumped parameter modeling dedicated to karst

hydrology. Systematic consideration of LCLU is thus not necessarily worthwhile in karst environments as it can bring contradictory results in terms of hydrological model performance. Further work should investigate both structural and parametric uncertainties related to the inclusion of LCLU in lumped parameter modeling in karst hydrology since LCLU changes may have strong impact on recharge processes as well as strong implications on groundwater vulnerability.

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CRediT authorship contribution statement

Vianney Sivel: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft.

Hervé Jourde: Supervision, Project administration, Funding acquisition, Writing - review & editing.

Daniel Bittner: Software, Writing - review & editing. **Beatrice Richieri**: Writing - review & editing.

David Labat: Writing - review & editing. **Andreas Hartmann**: Writing - review & editing. **Gabriele**

Chiogna: Writing - review & editing

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Appendix A

In a LuKARS model, areas with homogeneous infiltration conditions are implemented as distinct hydrological response units, called hydrotopes. A hydrotope is analogous to a bucket that has three discharge components: the quickflow component (Q_{hyd} [L^3T^{-1}]), a secondary spring discharge (Q_{sec} [L^3T^{-1}]), and the recharge (Q_{is} [L^3T^{-1}]). Q_{hyd} is considered a hydrotope-specific quickflow occurring in preferential flow paths (e.g. subsurface conduits). The quickflow bypasses the baseflow storage B and is directly transferred to the spring outlet. The quickflow starts, once a hydrotope-specific storage threshold (E_{max}) has been reached and stops after the hydrotope storage fall below a lower storage threshold (E_{min}). Q_{sec} integrates all flow components that do not arrive at the simulated karst spring and that are transferred outside the regarded recharge area, i.e. secondary spring discharge and overland flow (Tritz et al., 2011). Q_{is} is the discharge from one hydrotope to the underlying baseflow storage B that represents the process of groundwater recharge. Each hydrotope has 7 physical parameters, with length units L and time units T , that are as follows:

- k_{hyd} [L^2T^{-1}] is the discharge parameter for Q_{hyd} ,
- E_{min} [L] is the minimum storage capacity of a hydrotope,
- E_{max} [L] is the maximum storage capacity of a hydrotope,
- α [-] is the hydrotope-specific quickflow exponent,
- k_{is} [LT^{-1}] is the discharge parameter for Q_{is} ,
- k_{sec} [LT^{-1}] is the discharge parameter for Q_{sec} ,
- E_{sec} [L] is the activation level for Q_{sec}

Following the conceptual sketch from Bittner et al., (2018), the model solves the following discrete balance equations for each hydrotope i and for each time step n :

$$E_{i,n+1} = \max \left[0, E_{i,n} + \left(S_{i,n} - \frac{Q_{hyd,i,n} + Q_{sec,i,n} + Q_{is,i,n}}{a_i} \right) \Delta t \right] \quad (A.1)$$

Where E_i indicates the water level [L] in hydrotope i . S_i is the hydrotope-specific sink and source term as a mass balance of precipitation, evapotranspiration, and interception. Then, evapotranspiration is

615 considered using the formula from Oudin et al., (2005). $Q_{hyd,i}$ [L^3T^{-1}] represents the quickflow
 616 component (e.g. conduit flow), $Q_{sec,i}$ [L^2T^{-1}] refers to the secondary spring discharge, and $Q_{is,i}$ [L^2T^{-1}]
 617 is the groundwater recharge. The absolute area covered by a respective hydrotope is given by a_i
 618 [L^2].

$$E_{b,n+1} = \max \left[0, E_{b,n} + \left(\frac{\sum(Q_{is,i,n}) - Q_{b,n} - Q_{pumpB,n}}{A} \right) \Delta t \right] \quad (A.2)$$

619 is the balance equation for the baseflow storage B, where E_b indicates the water level [L] in the
 620 baseflow storage, $\sum(Q_{is,i,n})$ [L^3T^{-1}] indicates the cumulative flows from all hydrotopes to the baseflow
 621 storage, Q_b [L^3T^{-1}] indicates water that is transferred from the storage B to the spring, hence simulates
 622 the baseflow contribution from the phreatic aquifer system to the spring discharge, and Q_{pumpB} [L^3T^{-1}]
 623 indicates the groundwater abstraction in the aquifer. The variable A [L^2] stands for the entire
 624 recharge area. The discharge terms are computed as follows:

$$Q_{hyd,i,n} = a_i \frac{k_{hyd,i}}{l_{hyd,i}} \varepsilon_n \left[\frac{\max(0, E_{i,n} - E_{min,i})}{E_{max,i} - E_{min,i}} \right] \alpha_i \quad (A.3)$$

$$Q_{sec,i,n} = a_i k_{sec,i} \max(0, E_{i,n} - E_{sec,i}) \quad (A.4)$$

$$Q_{is,i,n} = a_i k_{is,i} E_{i,n} \quad (A.5)$$

$$Q_{b,n} = \begin{cases} [k_b * E_{b,n} + 0.2 * k_b * (E_{b,n} - ceil_B)] * A & \text{if } E_{b,n} \geq ceil_B \\ k_b * E_{b,n} * A & \text{if } E_{b,n} < ceil_B \end{cases} \quad (A.6)$$

625 $E_{max,i}$ [L] and $E_{min,i}$ [L] represent the upper and lower storage thresholds of the hydrotope i. $E_{sec,i}$
 626 [L] is the hydrotope-specific activation level for a secondary spring discharge. $k_{sec,i}$ [LT^{-1}], $k_{is,i}$
 627 [LT^{-1}] and k_b [LT^{-1}] are the specific discharge parameters for $Q_{sec,i}$ [L^3T^{-1}], $Q_{is,i}$ [L^3T^{-1}] and Q_b
 628 [L^3T^{-1}], respectively. $k_{hyd,i}$ [L^2T^{-1}] represents the specific discharge parameter for the quickflow of a
 629 hydrotope and $l_{hyd,i}$ [L] is the mean distance of hydrotope i to the adjacent spring, thus accounting for
 630 the relative location of the same hydrotope types in a specific recharge area. The ratio between $k_{hyd,i}$

631 and $l_{hyd,i}$ represents the hydrotope discharge coefficient and α_i is a hydrotope-specific exponent of
 632 the quickflow. The dimensionless connectivity/activation indicator ε is defined as follows:

$$\varepsilon_{n+1} = 0 \text{ if } \{\varepsilon_n = 0 \wedge \varepsilon_{i,n+1} < E_{max,i} \vee \varepsilon_n = 1 \wedge \varepsilon_{i,n+1} \leq E_{min,i}\} \quad (\text{A.7})$$

$$\varepsilon_{n+1} = 1 \text{ if } \{\varepsilon_n = 0 \wedge \varepsilon_{i,n+1} \geq E_{max,i} \vee \varepsilon_n = 1 \wedge \varepsilon_{i,n+1} > E_{min,i}\} \quad (\text{A.8})$$

633 To account for groundwater abstraction, the original equation for the baseflow compartment in the
 634 LuKARS model is modified as follows:

$$B_{n+1} = \max \left[0, B_n + \left(\frac{Q_{is,n} - Q_{b,n} - Q_{pumpB}}{A} \right) * \Delta t \right] \quad (\text{A.9})$$

$$Q_{b,n} = \begin{cases} \left[k_{b_{down}} * E_{b,n} + k_{b_{up}} * (E_{b,n} - threshold_B) \right] * A \text{ if } E_{b,n} \geq threshold_B \\ k_{b_{down}} * E_{b,n} * A \text{ if } E_{b,n} < threshold_B \end{cases} \quad (\text{A.10})$$

635 where B_n is the water level [L] in the baseflow compartment at the time step n , $Q_{is,n}$ is the total flow
 636 from all hydrotopes to the baseflow compartment [L^3T^{-1}], $Q_{b_{down}}$ is the flow from the linear baseflow
 637 compartment to the spring [L^3T^{-1}], $Q_{b_{up}}$ is the flow from the linear baseflow compartment
 638 corresponding to the overflow when the water level $B_n \geq threshold_B$, Q_{pumpB} is the groundwater
 639 abstraction discharge [L^3T^{-1}], A is the total recharge area [L^2].

640

641 **Appendix B**

642 The model is based on a structure available within the KarstMod modeling platform (Jourde et al.,
 643 2015; Mazzilli et al., 2019). The model consists of a two-level structure: (1) compartment E (higher
 644 level) and (2) compartments M and C (lower level). The mass-balance equations provided by Mazzilli
 645 et al. (2019) are applied.

$$\frac{dE}{dt} = P - ET - Q_{EM} - Q_{EC} \text{ if } E \geq 0 \quad (\text{B.1})$$

$$\frac{dC}{dt} = Q_{EC} + Q_{MC} \quad (\text{B.2})$$

$$\frac{dM}{dt} = Q_{EM} - Q_{MC} \quad (\text{B.3})$$

646 where

$$Q_{EM} = k_{EM} \times E(t)^{a_{EM}} \text{ if } E(t) > 0, \text{ otherwise } Q_{EM} = 0 \quad (\text{B.3})$$

$$Q_{EC} = k_{EC} \times E(t)^{a_{EC}} \text{ if } E(t) > 0, \text{ otherwise } Q_{EC} = 0 \quad (\text{B.4})$$

$$Q_{MC} = k_{MC} \times [M(t) - C(t)]^{a_{MC}} \quad (\text{B.5})$$

$$Q_{CS} = k_{CS} \times C(t)^{a_{CS}} \quad (\text{B.6})$$

647 Where P and ET are respectively rainfall and evapotranspiration [L], E(t), M(t) and C(t) are the water
 648 levels in the compartments E (epikarst), M (matrix) and C (conduit), k_{AB} is the recession coefficient
 649 associated with the flow from compartment A (either E, M, or C) to compartment B (either M, C, or
 650 L) or to the outlet S and Q_{AB} [L^3T^{-1}] is the discharge from A to B. Discharge in [L^3T^{-1}] is computed by
 651 the product of Q_{AB} [L^3T^{-1}] with the total surface of the recharge area [L^2]. To reproduce the different
 652 flow behavior between epikarst (E) and the deeper compartments conduit (C) and matrix (M),
 653 emptying exponents are fixed as $a_{EM} = a_{MC} = 1$, $a_{EC} = 2$ and $a_{CS} = 4$ (Sivelle et al., 2019).

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			Climate		Geology	LCLU
	Recharge Area (km ²)	Mean annual discharge (m ³ /s)	Mean Annual Precipitation (mm)	Mean Annual ET (mm)		
Kerschbaum	2.5	0.034	mean = 1405 from 1040 to 1820	mean = 814 from 723 to 984	Dolostone Triassic	Dolomite quarries – 4% Bluegrass-Beech Forest – 13% White Sedge-Beech Forest – 56% Christmas Rose-Beech Forest – 27%
Oeillal	43.2	0.14	mean = 570 from 300 to 1150	mean = 1380 from 875 to 1540	Limestone Upper and Lower Jurassic	Urban area and limestone quarries – 6.5% Wine yard and agricultural plots – 30.8% Coniferous forest – 62.7 %
Baget	13.2	0.45	mean = 1000 from 650 to 1350	mean = 810 from 680 to 940	Limestone and dolostone Jurassic to Cretaceous	Non-karstic impluvium - 20% Agricultural plots - 3% Poor vegetal cover - 5% Hardwood trees forest - 72%

Table 1 Information about the karst catchment

Catchment	Model	Ref.	Upper level				Lower level
			Hyd. 1	Hyd. 2	Hyd. 3	Hyd. 4	
Oeillal	LK_01	-	Complete recharge area				1 compartment with linear discharge law
	LK_02	Sivelle et al., (2021)	Impervious zone	Infiltration zone	-	-	
	LK_03	-	Impervious zone	Wine yard Agricultural lots	Forest	-	
Kerschbaum	LK_01	-	Complete recharge area				1 compartment with linear discharge law
	LK_02	-	Quarries	Infiltration zone	-	-	
	LK_03	-	Quarries	White Sedge-Beech Forest	Christmas Rose-Beech Forest + Wood Barley-Beech Forest	-	
	LK_04	Bittner et al., (2018)	Quarries	White Sedge-Beech Forest	Christmas Rose-Beech Forest	Wood Barley-Beech Forest	
Baget	LK_01	-	Complete recharge area				1 compartment with linear discharge law
	LK_02	-	Non-karstic impluvium	Karstic impluvium	-	-	
	LK_03	-	Non-karstic impluvium	Poor vegetation cover	Agricultural plot + Forest	-	
	LK_04	-	Non-karstic impluvium	Poor vegetation cover	Agricultural plot	Forest	
	LK-KM_01	-	Complete recharge area				1 compartment with linear discharge law
	LK-KM_02	-	Non-karstic impluvium	Karstic impluvium	-	-	
	LK-KM_03	-	Non-karstic impluvium	Poor vegetation cover	Agricultural plot + Forest	-	
	LK-KM_04	-	Non-karstic impluvium	Poor vegetation cover	Agricultural plot	Forest	
	KM	Sivelle et al., (2019)	1 compartment with 2 different discharge law through the compartments of the lower level				2 interconnected compartments M and C with nonlinear discharge laws

900 **Table 2** Information about the model structures tested along with the three-karst catchment (Baget, Oeillal and Kerschbaum). Some of the mode structure
901 were already published in former studies.

	Period	Calibration	Validation	Wobj	Reference
Baget	from to	01/10/1970 30/09/1980	01/10/1980 31/12/2016	$0.9 \times NSE(Q) + 0.1 \times BE(Q)$	(Sivelle et al., 2019)
Kerschbaum	from to	01/01/2006 31/12/2006	01/01/2007 31/12/2007	$NSE(Q)$	(Bittner et al., 2018)
Oeillal	from to	19/09/2018 25/04/2020	01/01/1987 31/12/2017	$0.75 \times KGE(Q) + 0.25 \times BE(Q)$	(Sivelle et al., 2021)

Table 3 Calibration periods, validation periods and objective function (Wobj) for hydrological models. Calibration and validation periods and objective function are based on former references. BE: Balance Error, NSE: Nash-Sutcliffe Efficiency, KGE: Kling-Gupta Efficiency and Q: spring discharge

902

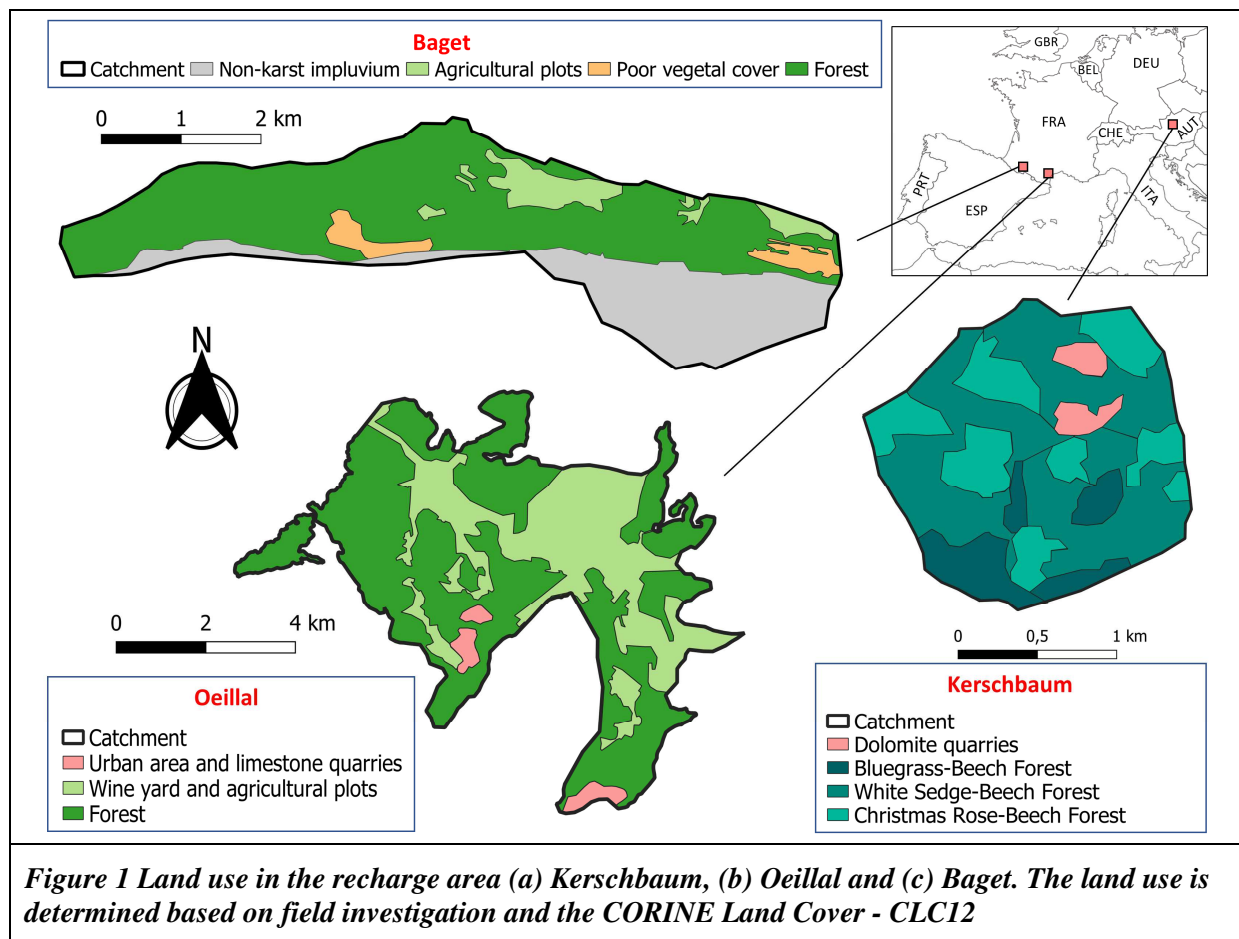
903

		Kerschbaum				Oeillal			Baget - LuKARS				Baget - Coupled LuKARS/KarstMod			
		1	2	3	4	1	2	3	1	2	3	4	1	2	3	4
Hydrotope 1	Ra	2,5	0,1	0,1	0,1	42,3	2,7	2,7	13,2	2,64	2,64	2,64	13,2	2,64	2,64	2,64
	L	1000	550	550	550	7300	7300	5600	5000	2000	2000	2000	5000	2000	2000	2000
	khy	320,817	0	0	0	426,80	0	0	1840100	593920	1727320	1083560	0	0,965	0	0
	Emin	38,242	0	0	0	117,85	0	0	762,65	894,76	632,54	570,49	0	95,78	31,36	31,36
	Emax	160,075	1	1	1	191,63	1	1	1127,94	1194,28	1496,22	1157,98	1	179,74	495,75	495,75
	alpha	0,547	0	0	0	0,28	0	0	1,98	1,34	1,015	1,25	1	5,81	2,61	2,61
	kis	0,003	0	0	0	0,02	0	0	0,0001	0	0	0	1	0	0	0
	ksec	0,488	0	0	0	5,35	3,9	3,9	0	0	0	0	0	0	0	0
	Eloss	233,109	0	0	0	162,76	0	0	10000	100000	100000	100000	100000	100000	100000	100000
Hydrotope 2	Ra	2,35	0,325	0,325		39,6	13,0		10,56	1,056	0,396		10,56	1,056	0,396	
	L	971	1600	1600		5900	6200		5000	3000	2000		5000	3000	2000	
	khy	118,77	517,86	684,21		919,15	224,87		1483800	1605420	2429460		0	0	0	
	Emin	2,98	14,09	34,89		110,16	69,70		744,07	195,32	104,48		0	0	0	
	Emax	62,83	55,55	73,65		193,42	148,99		1652,6	640,97	140,08		1	1	1	
	alpha	1,44	1,47	1,54		0,38	0,44		1,25	1,21	1,04		1	1	1	
	kis	0,04	0,03	0,12		0,02	0,29		0,0001	7,6	7,22		0,302	0,46	0,46	
	ksec	0,28	0,77	0,92		16,08	14,60		0	0	0		0	0	0	
	Eloss	35,00	27,83	64,10		177,17	16,29		100000	100000	100000		100000	100000	100000	
Hydrotope 3	Ra		2,075	1,4			26,5			9,504	0,66			9,504	0,66	
	L		920	900			6800			5000	3100			5000	3100	
	khy		99,9284	105,1630			740,60			3413900	2116618			0	0	
	Emin		46,6049	8,0584			97,94			532,55	432,55			0	0	
	Emax		148,9139	114,7194			159,40			1357,07	1153,07			1	1	
	alpha		0,8078	0,9812			1,81			1,25	1,25			1	1	
	kis		0,0035	0,0033			0,04			1,02	1,02			0,31	0,35	
	ksec		0,0298	0,0465			87,34			0	0			0	0	
	Eloss		211,2942	171,7668			118,10			100000	100000			100000	100000	
Hydrotope 4	Ra			0,675												9,504
	L			960												5000
	khy			167,593												0
	Emin			100,676												0
	Emax			224,941												1
	alpha			0,489												1
	kis			0,001												0,21
	ksec			0,024												0
	Eloss			419,301												100000
Lower level	kMS_bot	0,00099	0,00098	0,00092	0,00092	0,06134	0,02880	0,06670	0,00774	0,04050	0,09233	0,04032				
	kMS_top					0,00844	0,00886	0,00822								
	M_min					2,38138	4,93496	2,57138								
	XEC												0,75	0,87	1	1
	Xhy												1	0,78	0,626	0,626
	aMS												1	1	1	1
	kCS												0,0001	0,00483	0,00676	0,00676
	aCS												4	4	4	4
	kMC												0,39	0,559	0,634	0,634
	aMC												1	1	1	1

Table 4 Model parameters for LuKARS model over Kerschbaum, Oeillal and Baget and the coupled LuKARS/KarstMod model for the Baget catchment. Parameter description is given in Table 2.

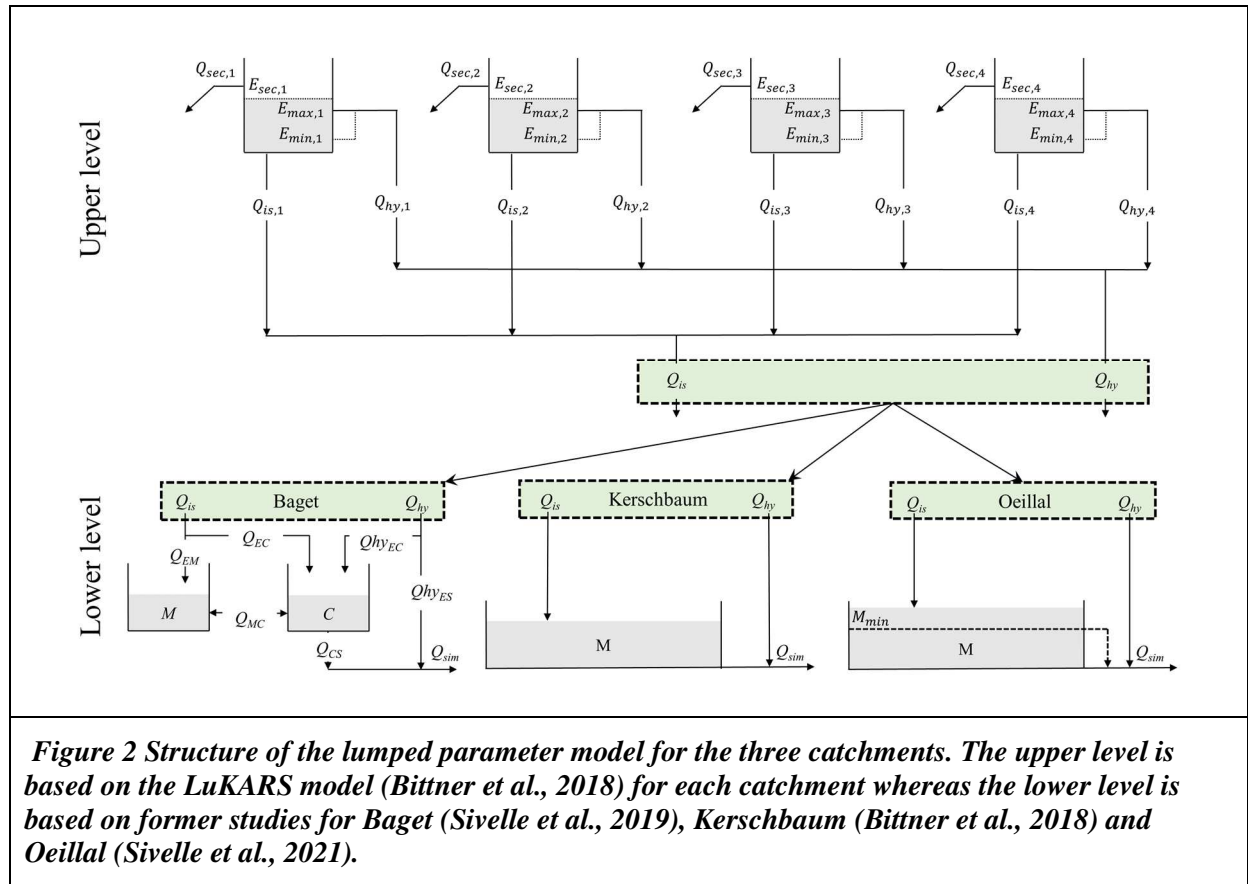
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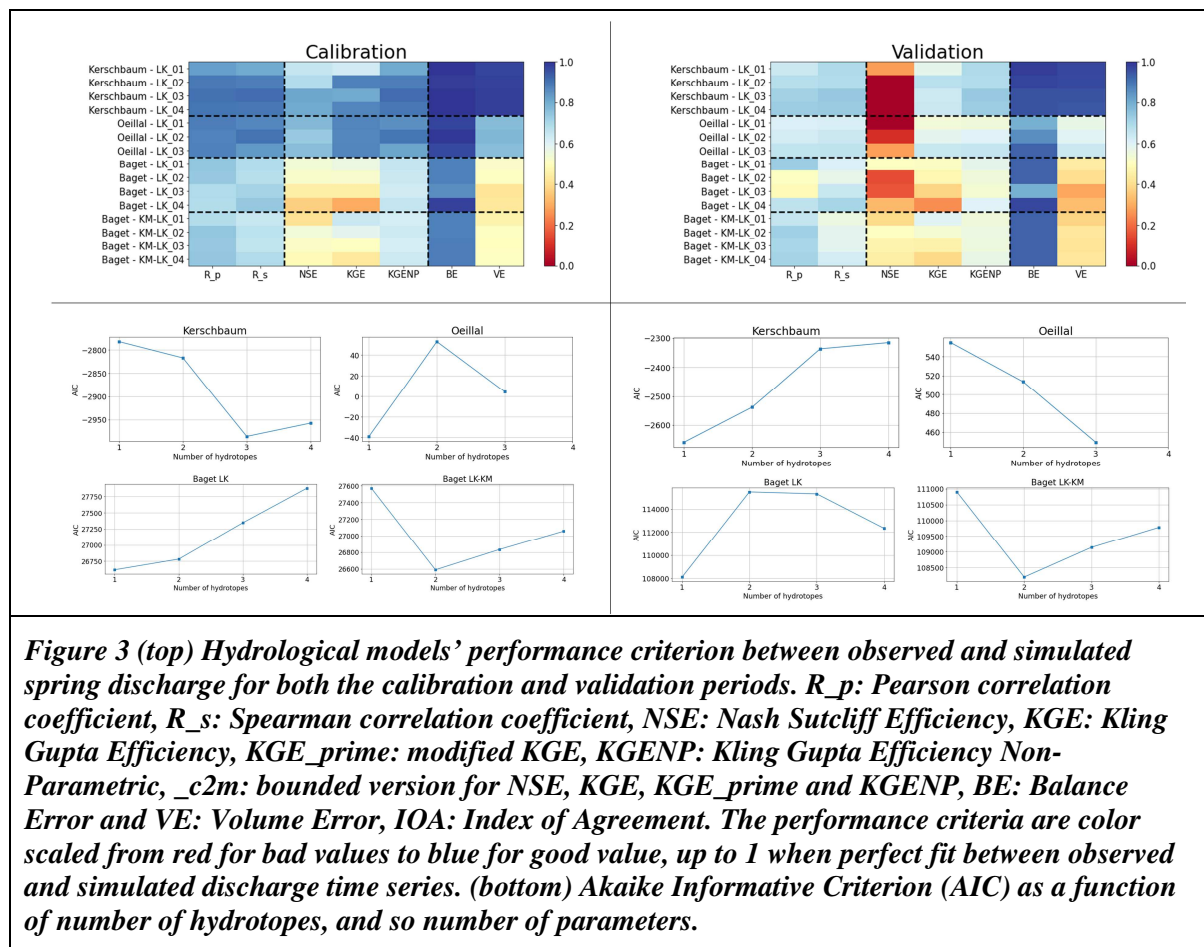
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906

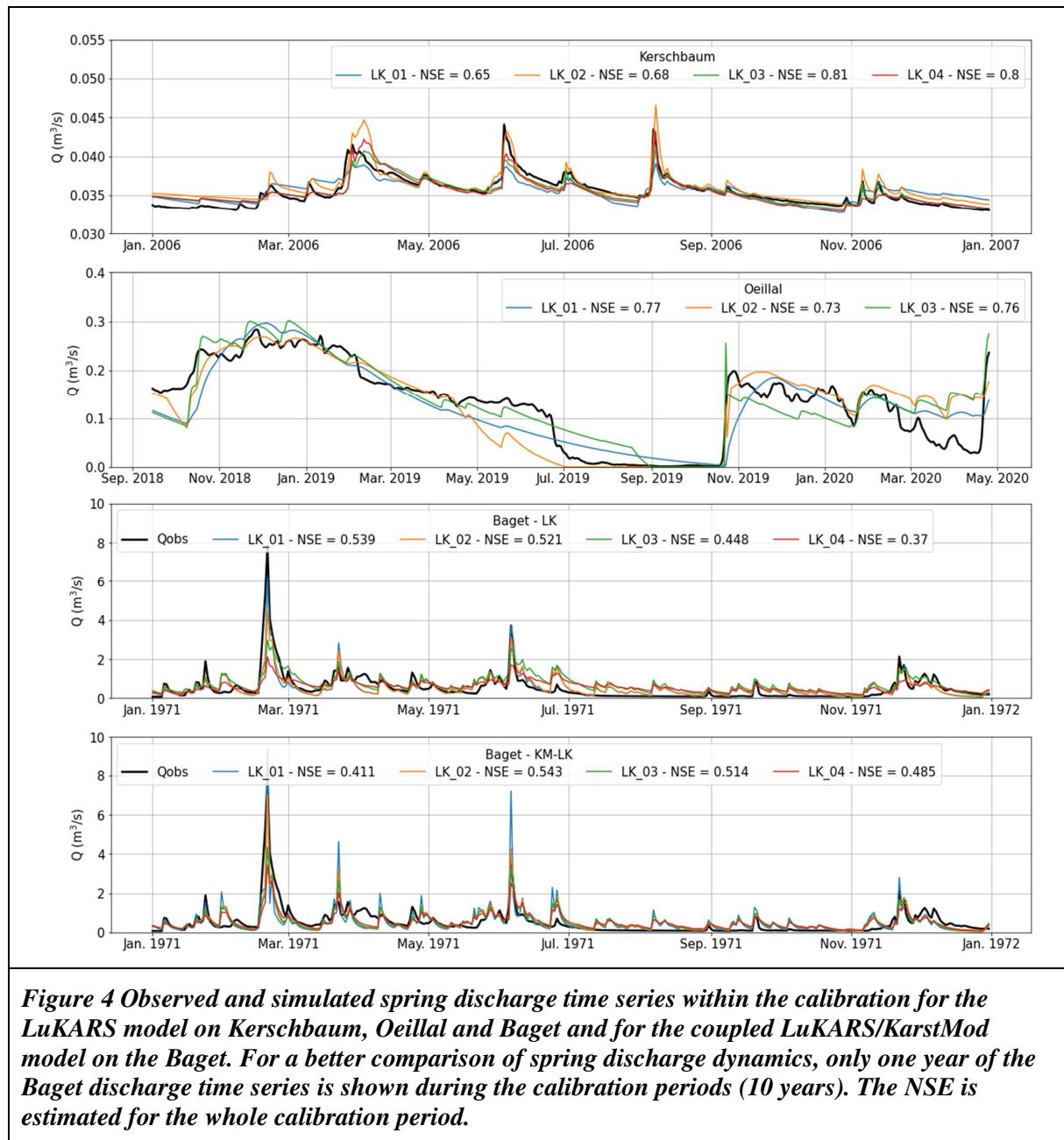
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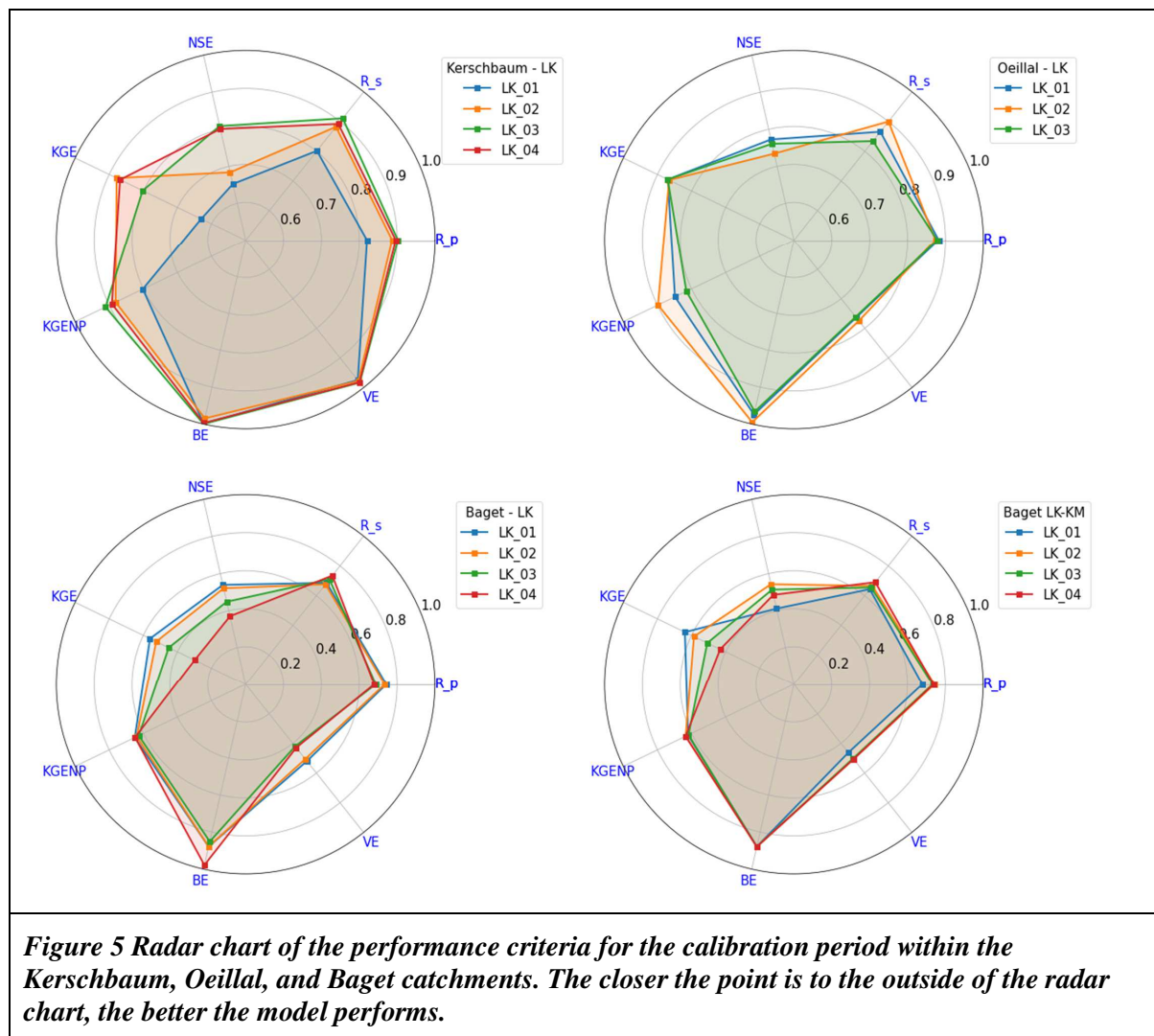
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911



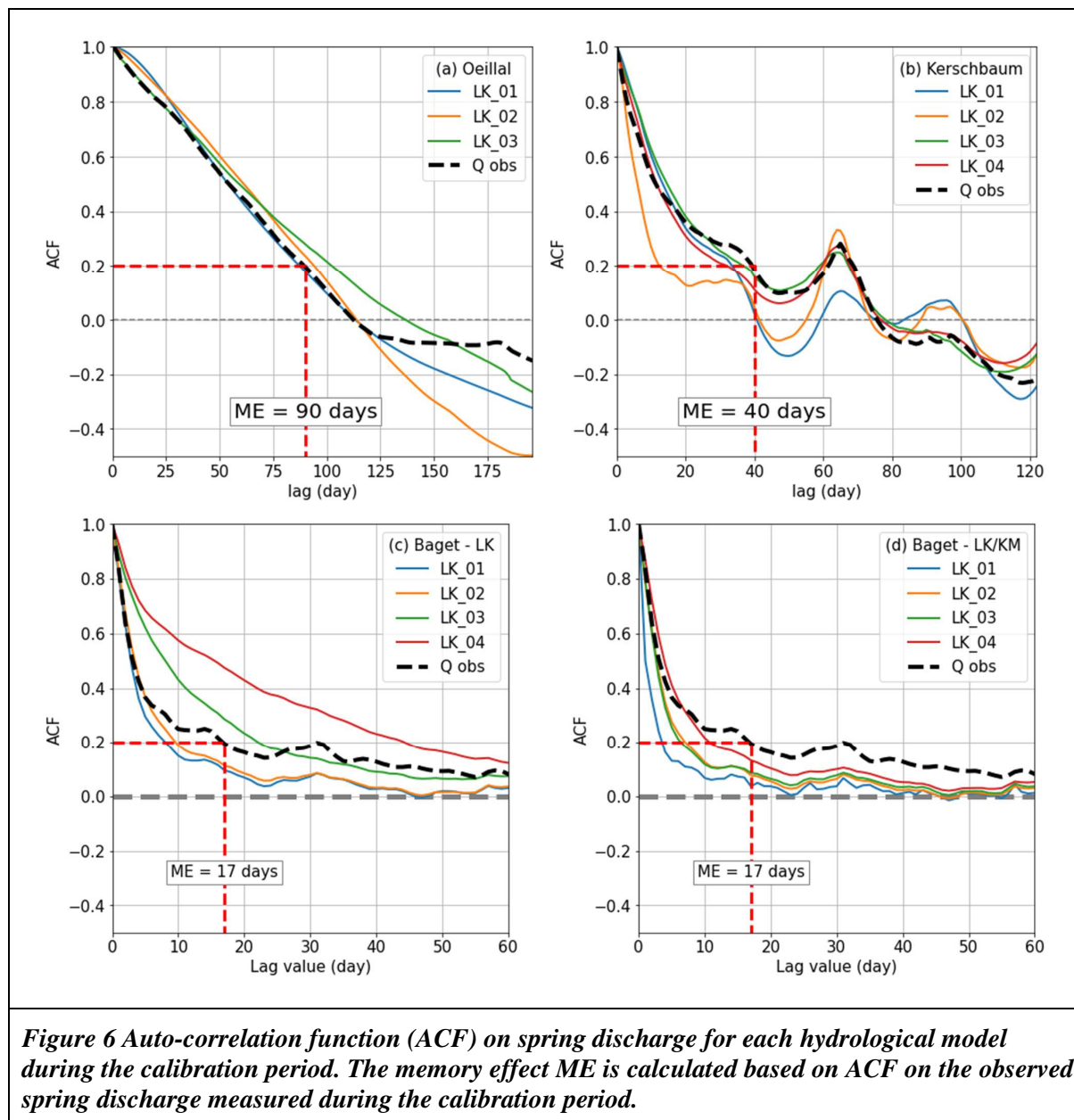
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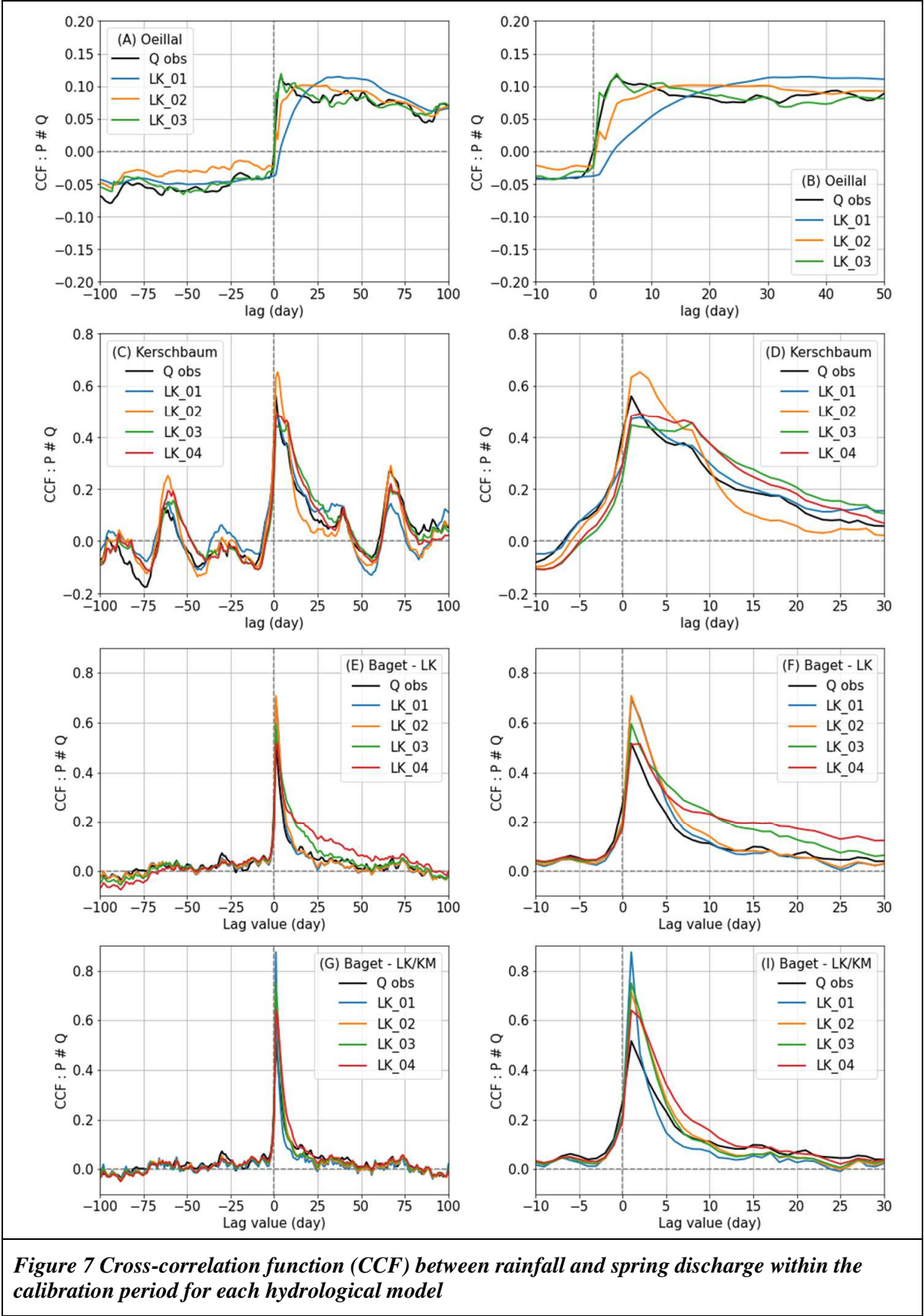
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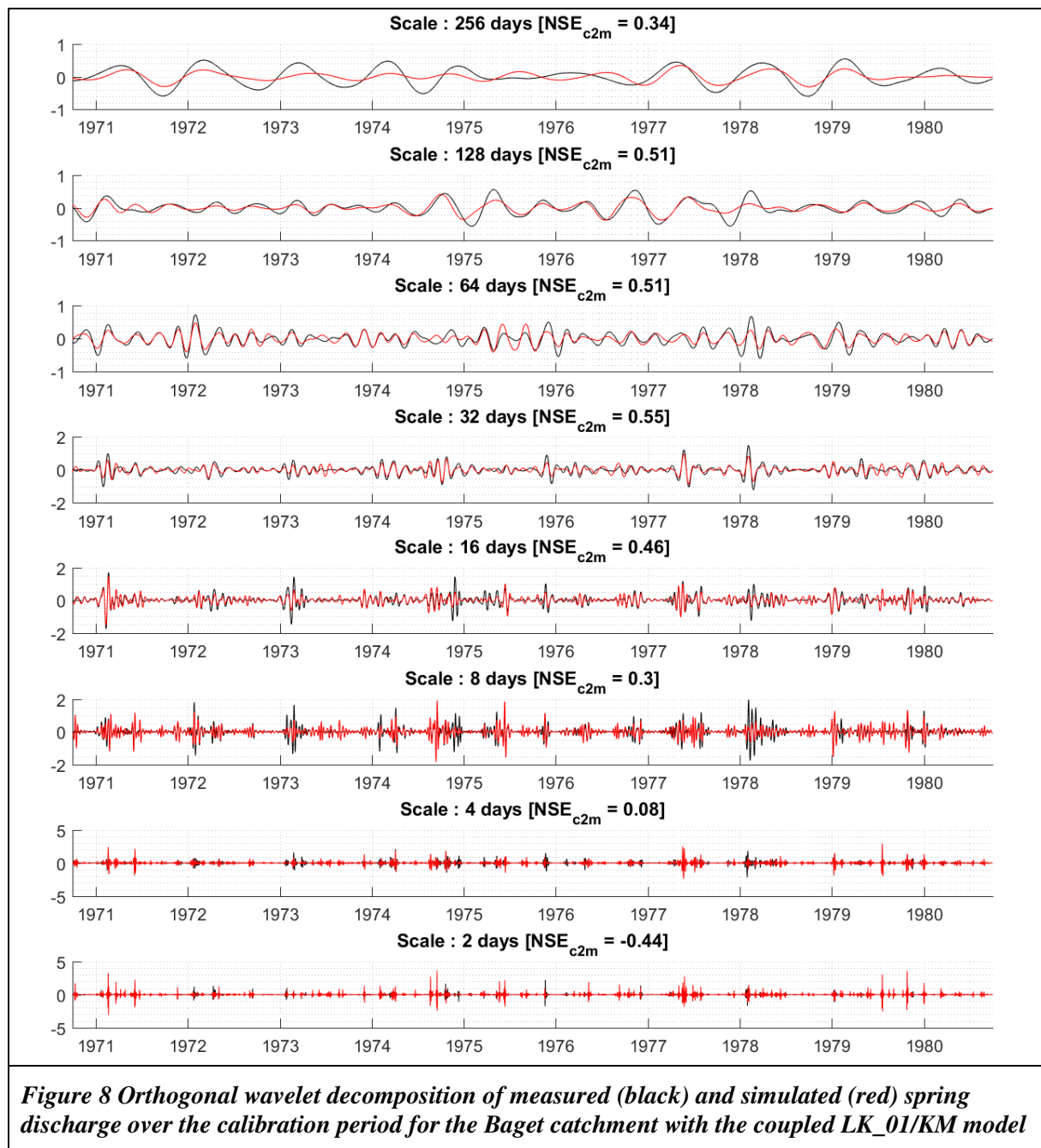
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917



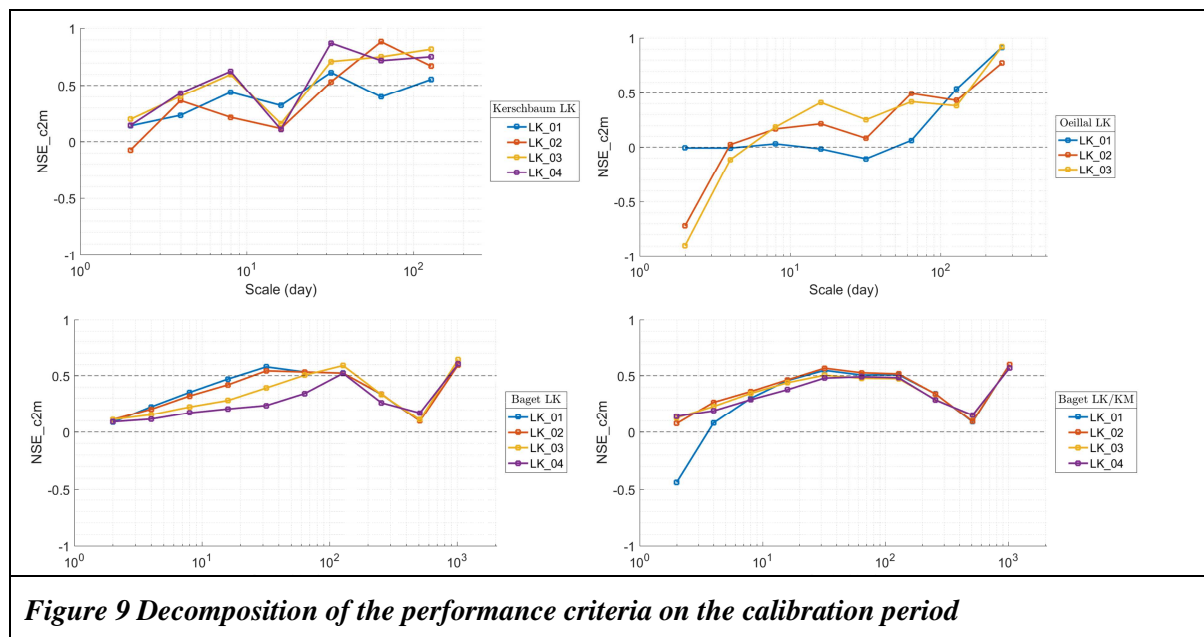
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