

Integrating field work, large sample hydrology and modeling to inform (inter)national governance of karst water resources

Andreas Hartmann^{1,2}, Yan Liu¹, Tunde Olarinoye¹, Romane Berthelin¹, Vera Marx¹

¹ Chair of Hydrological Modeling and Water Resources, University of Freiburg, Friedrichstrasse 39, Freiburg, 79098, Germany

² Department of Civil Engineering, University of Bristol, Bristol, UK

Corresponding author:

Andreas Hartmann

E-mail: andreas.hartmann@hydmod.uni-freiburg.de

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Abstract

Substantial changes of climate and land use are projected in many karst regions in the world for the next decades. Despite these projections, only few studies have been performed to quantify the impact of climate change and land use change on karst water resources. This is mainly due to a lack of observations of the karstic recharge and groundwater dynamics, which is prohibiting the development large-scale karst simulation models. Here we present the advances of the first global effort to develop a simulation tool to support (inter)national governance of karst water resources. Using a global soil moisture monitoring program and a global database of karst spring discharges, we evaluate the simulations of a preliminary global karstic groundwater recharge model. We show that soil moisture is a crucial variable to better distinguish recharge dynamics in different climates and for different land cover types. Analyzing the global dataset, we find that mean discharge volumes, their variability and the recharge areas are showing similar variability for a large range of altitudes. Comparing the model simulations with the newly collected observations, indicates that (1) improvements of the recharge model are still necessary to obtain a better representation of different land cover types and snow processes, and (2) there is a need to incorporate groundwater dynamics. Applying and strictly evaluating these improvements in the model will finally provide a tool to identify hot spots of current or future water scarcity in the karst regions around the globe thus supporting national to international water governance.

Keywords

Karst, water resources, soil moisture, spring discharge analysis, groundwater recharge, global simulation model, model evaluation, water governance

43 **1. Introduction**

44 In many countries karst groundwater is the dominant or even the only available source of
45 fresh water (Stevanović 2019). Climate models indicate that in the next 100 years, karst
46 regions will experience a strong increase of temperature and a serious decrease of
47 precipitation in more Southern latitudes (Hartmann et al. 2014). The potential changes may
48 significantly affect hydrological regimes (Ferguson and Gleeson 2012) and may increase
49 stress on karst water resources. A decrease of water availability can have strong negative
50 impacts on the wellbeing of agriculture, tourism, infrastructure, energy supply, ecosystems
51 and biodiversity. To be prepared, stakeholders and policy makers have to understand the
52 impacts of climate, land use and population change on karst water resources at national and
53 international scales. Policies to ensure an optimal level of adaptation and mitigation can only
54 be developed if quantitative and reliable estimates of potential changes to karst water
55 resources are available at the same scales. Even though strong progress in estimating global
56 water stress was made in the previous years (Wada et al. 2014; Döll et al. 2016; de Graaf et
57 al. 2019), most large-scale modeling studies did not consider the particularities of karst
58 hydrogeology and therefore have limited applicability for water resources management
59 (Hartmann 2016).

60 The karstic surface and subsurface heterogeneity results in a complex interplay of preferential
61 and diffuse flow patterns. Overall, the hydrological behavior of karst systems shows a duality
62 in its process and storage dynamics (Király 1998): (1) Duality of infiltration and recharge
63 processes: diffusive, slow infiltration and recharge into the matrix, and concentrated, rapid
64 infiltration and recharge into the conduits. (2) Duality of the subsurface flow field: low flow
65 velocity in the matrix, and fast flow velocity in the karst conduits. (3) Duality of discharge
66 conditions: low and continuous discharge during dry periods when the system is dominated
67 by flow through the matrix, and high discharge with high temporal variability during rainfall
68 events when flow through the conduits is dominant. Karstic groundwater flow and discharge
69 have been intensely studied by hydrogeologist (Goldscheider and Drew 2007; Ford and
70 Williams 2013), while recharge generation processes at the shallow subsurface of the karst,
71 i.e. the soil and epikarst, received less attention (Berthelin and Hartmann 2020).

72 Most karst hydrology models are applied at the scales of individual aquifers (Hartmann et al.
73 2014) using varying degrees of complexity (Teutsch and Sauter 1991; Sauter et al. 2006;
74 Kovacs and Sauter 2007; Ghasemizadeh et al. 2012; Hartmann et al. 2014). Distributed karst
75 models provide spatially explicit information on groundwater pressure heads and
76 groundwater flow. They are mostly applied at well explored test sites (Chen and Goldscheider

2014; Oehlmann et al. 2014) or were used for theoretical calculations of general behavior of karst hydrology (Covington et al. 2009; Reimann et al. 2014). Lumped karst modeling approaches conceptualize the physical processes at the scale of the whole karst system without being spatially explicit. They consider (1) internal and external runoff (e.g., Jukic and Denic-Jukic, 2009), (2) epikarst storage and flow processes (e.g., Tritz et al. 2011), (3) groundwater storage and flow in karst conduits and the matrix (e.g. Mazzilli et al. 2019), (4) varying surface and subsurface recharge areas (e.g., Le Moine et al. 2007), and (5) drainage through several springs (e.g., Rimmer and Salingar 2006).

Beyond the scale of individual aquifers, only few studies on quantifying karst water resources can be found. Using observations of specific discharge at multiple sites with high data reliability and precipitation deviations and catchment elevation, Malard et al. (2016) could implement a regional extrapolation of karstic groundwater recharge in Switzerland. Estimating recharge from the difference of mean annual precipitation and mean annual actual evapotranspiration, Allocca et al. (2014) regionalized karstic groundwater recharge over the southern Apennines in Italy using the areal fractions of limestone and regions without superficial discharge (endorheic areas) as predictors. Huang et al. (2019) showed that terrestrial water storage estimates by the Gravity Recovery and Climate Experiment (GRACE) could be used to quantify the discharge reaction of karst aquifers over the large karst regions of Southwest China.

To predict the impact of climate change and land use changes on karst water availability at larger scales, simulation models are necessary that combine spatial extrapolation or regionalization schemes with the process-oriented model structures. With the aim of quantifying the water balance of the karst dominated island of Crete, Greece, Malagò et al. (2016) developed an extension of the SWAT model (Neitsch et al. 2011) to consider the duality of karstic groundwater. They used a hydrological similarity approach to run their model at the scale of the entire island. Hartmann et al. (2015) used the Concept of Hydrologic Landscapes (Winter 2001) to set up a continental karstic groundwater recharge model over Europe, Northern Africa and the Middle East using a karst specific modelling concept that was previously developed and tested at local scales (Hartmann et al. 2012). Coupled with climate projections (CMIP5, Taylor et al. 2012), the model could be used to estimate future groundwater recharge (Hartmann et al. 2017).

But yet no approaches to simulate karst water availability exist at the global scale. On the one hand, a lack of observations of karstic groundwater dynamics at the global scale prohibits the extrapolation or regionalization of local information to national or international scales. On

111 the other hand, a lack of conceptual understanding of recharge generation in the karstic
112 shallow subsurface, especially outside the mid latitude regions of Northern America and
113 Europe, still limits the reliability of large-scale karst recharge models. For those reasons,
114 modeling approaches to provide reliable estimates of karst water resources at the global scale
115 are still not available.

116 This paper presents the advances of the first global effort to develop a large-scale simulation
117 tool to estimate karst water resources at a global scale to support national and international
118 decision making. Involving wide parts of the Karst Commission of the International
119 Association of Hydrogeologists (IAH), an international research project was launched to
120 provide (1) a better understanding of near-surface karst processes by a global soil moisture
121 monitoring program, (2) new methods to derive regional information karstic of aquifer
122 properties from large numbers of catchment scale observations using a new global database
123 of karst spring discharges, and (3) a systematic approach to incorporate such new
124 understanding into a globally applicable karst simulation model.

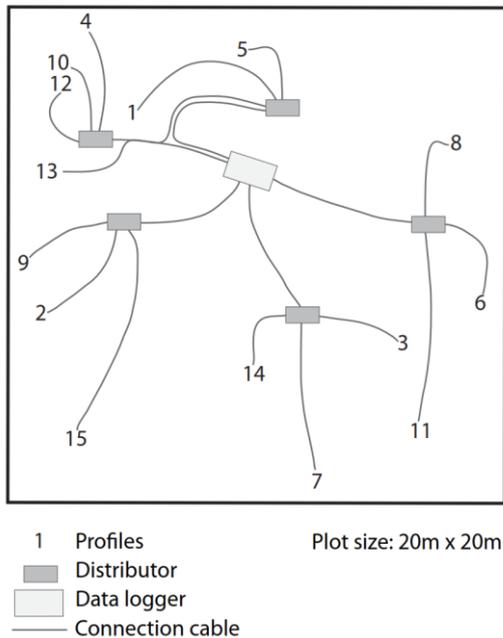
125 **2. Data & Methods**

126 **2.1. Setup of a global monitoring program to characterize soil and** 127 **epikarst processes**

128 Previous work already showed that additional process understanding can be gained by
129 monitoring spatiotemporal variabilities of shallow subsurface hydrodynamics (Penna et al.,
130 2014; Rinderer et al., 2015). Applied in karst regions such approaches can provide more
131 understanding of the local surface heterogeneity and its implication for hydrological
132 modeling. For that reason, a global soil moisture monitoring program was established to
133 monitor soil moisture dynamics at a high frequency, at different locations and at different
134 depths. In total > 400 soil moisture probes were installed across five sites located in Puerto
135 Rico (tropical climate), Spain (Mediterranean climate), the UK (oceanic climate), Germany
136 (mountainous climate), and Australia (semi-arid climate). At each site, the probes were split
137 over two different land cover types (forest and grassland) to cover different vegetation cover
138 types.

139 To account for spatial variability and to minimize the impact of subjectivity when choosing
140 the locations to install the probes, 15 locations for soil profiles were randomly sampled from
141 a uniform distribution at two 20m × 20m plots at the forest and the grassland areas of each of
142 our study sites. At each location, vertical profiles with three soil moisture probes were
143 installed at 5 cm, 10 cm and at the boundary between soil and epikarst (80 cm max). Each

144 profile is connected to a logger that records soil moisture at 15-minutes resolution (Figure 1).
145 In addition, each of our five sites has its own climate station.



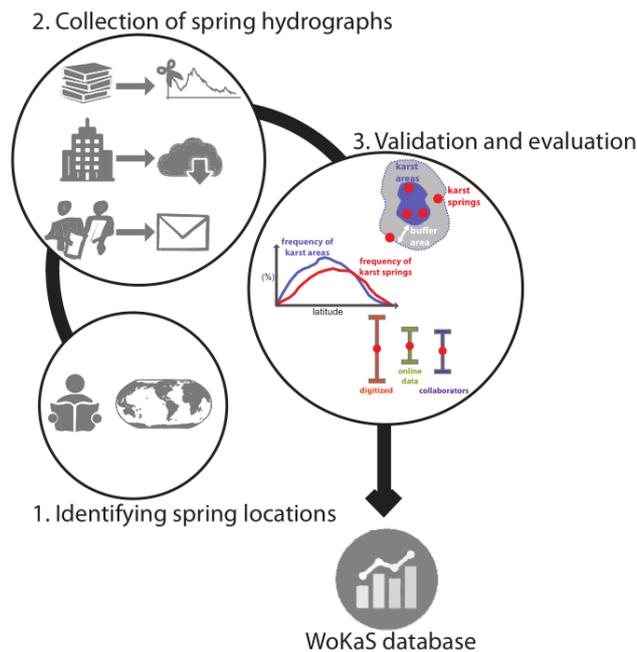
146
147 **Figure 1: Distribution of soil moisture probe profiles at one of the 20m × 20m plots (adapted from Berthelin et al.**
148 **2020)**

149 **2.2. Creation of a global database of karst spring discharges to analyses** 150 **karstic groundwater dynamics**

151 Methods to regionalize information from sites with better data availability (see for instance
152 the Precision in Ungauged Basins initiative, Sivapalan 2003; Blöschl et al. 2011) are still
153 limited given the particular complexity of karst systems. Analyzing large data sets of karst
154 system observations would allow for a more comprehensive understanding of regional and
155 global differences of karst system properties. However, an assemblage of karst system
156 observation datasets that would encourage such comparative exercise on larger scales is
157 scarce. There is a need for compilation and analysis of all available karst catchment scale
158 information around the globe.

159 For this reason, we directed our efforts towards the development of a global database of karst
160 spring observations, which would improve access to karst datasets. A framework for the
161 development of the World's Karst Spring (WoKaS) hydrograph database was developed
162 (Figure 2), involving (1) the identification of karst spring locations, (2) the collection of spring
163 discharge observations, and (3) the validation of the collected datasets. The previously
164 published World Karst Aquifer Map (WOKAM, Chen et al. 2017) was used to support the
165 identification of countries with carbonate rock, karst spring names and locations. An
166 extensive literature review of karst hydrology publications was conducted to further expand

167 the survey range. Discharge observations of the identified karst springs were extracted from
168 publications and national hydrological databases. In addition, a substantial fraction of the
169 observations was provided by individual researchers and members of the IAH Karst
170 Commission. We evaluated the accuracy and veracity of all collected spring locations as karst,
171 as well as representativeness of the datasets over the entire globe, which is described in more
172 detail in WoKaS data descriptor (Olarinoye et al. 2020).



173

174 **Figure 2: Data collection procedure for the WoKaS database (adapted from Olarinoye et al. 2020)**

175 For our preliminary analysis, we classify the collected datasets based on elevation, which has
176 been a simple and useful way to compare hydrological system characteristics, especially for
177 analyzing average behavior and variability of recharge and discharge volumes (Stoelzle et al.;
178 Malard et al. 2016). Five classes of springs defined from their elevations in meters above sea
179 level are: $L1 \leq 400\text{m}$, $400\text{m} < L2 \leq 800\text{m}$, $800 < L3 \leq 1200\text{m}$, $1200\text{m} < H1 \leq 1600\text{m}$, and
180 $H2 > 1600\text{m}$. The long-term mean discharges and their coefficient of variation (CV) were
181 calculated. Average precipitation values of the spring locations were computed using the
182 GLDAS precipitation datasets (Table 1). With the precipitation information and the simulated
183 recharge values obtained from the model described in the following subsection, we estimated
184 the recharge rates and recharge area of those WoKaS springs that had at least twelve months
185 of discharge observations.

186 **2.3. Setup of a preliminary global karst recharge model to quantify water** 187 **availability**

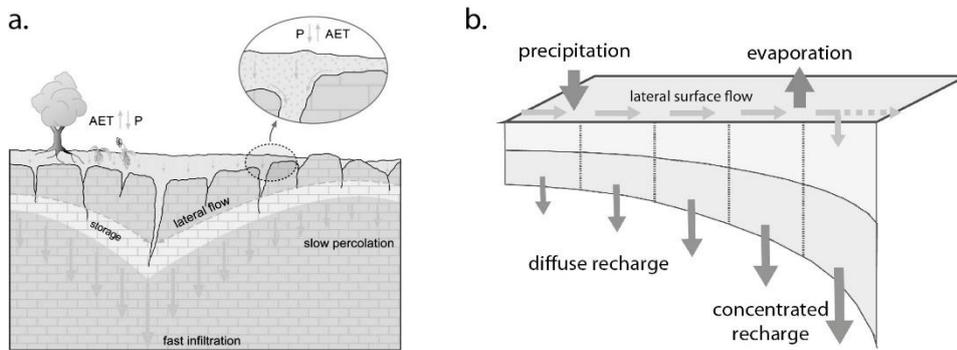
188 At larger scales the lack of data increases and additional uncertainties arise, since large-scale

189 models are commonly run on grid, while observations are available at point or catchment
 190 scale. Hence, a systematic approach to optimize the incorporation of local and catchment
 191 scale karst observations into the development and evaluation of a large-scale karst model is
 192 needed. For that reason, a global version of a previously published large-scale karst recharge
 193 model (Hartmann et al. 2015) was developed. The model simulates karst recharge processes
 194 based on the general conceptual model of the soil and the epikarst (Figure 3a, Williams 1983;
 195 Berthelin and Hartmann 2020) accounting for localized runoff, preferential infiltration,
 196 evapotranspiration from the soil, and vertical percolation from the epikarst layer towards the
 197 groundwater. In order to incorporate karstic heterogeneity, the model assumes distributions
 198 of subsurface properties such as soil and epikarst storage capacities, or epikarst hydraulic
 199 properties. In the model, these are distributed over N horizontally parallel model
 200 compartments (Figure 3b):

201
$$S_{\max,i} = S_{\max,N} \left(\frac{i}{N} \right)^a \quad (1)$$

202
$$K_{\text{epi},i} = K_{\text{epi},1} \left(\frac{N-i+1}{N} \right)^a \quad (2)$$

203 $S_{\max,i}$ [mm] is the soil or epikarst storage capacity of model compartment i , $S_{\max,N}$ [mm] is the
 204 overall maximum storage capacity of the soil or the epikarst, $K_{\text{epi},i}$ [d] is the storage constant
 205 of the epikarst at model compartment i , $K_{\text{epi},1}$ [d] is the storage constant of the epikarst at
 206 model compartment 1, and a [-] is a dimensionless shape factor. With these equations the
 207 water balance of a soil and a epikarst layer are calculated at a daily time step in each model
 208 compartment. Localized runoff towards model compartments with higher vertical infiltration
 209 capacity is initiated when soil and epikarst reach saturation. That way, weak to moderate
 210 rainfall events will mostly produce diffuse recharge and/or evapotranspiration, while strong
 211 rainfall events will result in concentrated recharge and lower fractions of precipitation are
 212 turned into evapotranspiration (Figure 3b).



214 **Figure 3: (a) Conceptual visualization of karstic recharge process (adapted from Berthelin and Hartmann 2020) and**
 215 **(b) sketch of the karst recharge model (adapted from Hartmann et al. 2015)**

216 Using freely available datasets (Table 1), the model is run over all karst regions in the world
 217 (obtained from Chen et al. 2017; Goldscheider et al. 2020) with daily forcings of precipitation
 218 and potential evapotranspiration obtained by the Priestley–Taylor equation (Priestley and
 219 Taylor 1972) obtained from (Miralles et al. 2011; Martens et al. 2017). It is run from 1990 to
 220 2019 at a $0.25^\circ \times 0.25^\circ$ spatial resolution where the first two years are used as a warm-up
 221 period. Other than its application at the continental scale (Hartmann et al. 2015), the
 222 preliminary global karst recharge model is not (yet) calibrated with observations of soil
 223 moisture and actual evapotranspiration, but it is run with 250 parameter sets sampled from a
 224 prior distribution using mean soil and mean epikarst storage capacities of 0-1250 mm and 20-
 225 700 mm, respectively, mean epikarst storage confidents of 0-50 days and a shape factor a of
 226 0-6. The variability of 250 resulting recharge simulations for each grid cell therefore
 227 represents the simulation uncertainty of this preliminary model application.

228 **Table 1: Datasets of precipitation, temperature and potential evapotranspiration that are used to drive the global**
 229 **karst recharge model**

Forcing	Product	Temporal resolution	Spatial resolution (Lat × Lon)	Time period	Reference
Precipitation (P), Temperature (T)	GLDAS	Daily (3-hourly)	$0.25^\circ \times 0.25^\circ$	1990-2019 ^a	(Rodell et al. 2004)
Potential evapotranspiration (PET)	GLEAM	Daily	$0.25^\circ \times 0.25^\circ$	1990-2019 ^b	(Miralles et al. 2011; Martens et al. 2017)

230 ^a Data of 1990-2014 is in daily resolution, while data of 2015-2019 is in 3-hourly resolution, where
 231 the mean temperature over a day is calculated using the 3-hourly temperature and the daily
 232 precipitation is obtained by aggregating the 3-hourly precipitation over a day.

233 ^b Potential evapotranspiration of 1990-2018 is directly provided by GLEAM, while the PET of 2019
 234 is computed by taking account of the PET variation in each month (data in every month over 1990-
 235 2018) and the correction by the daily temperature of 2019.

236
 237 **2.4. Evaluation of the global model with the soil moisture and spring**
 238 **discharge observations**

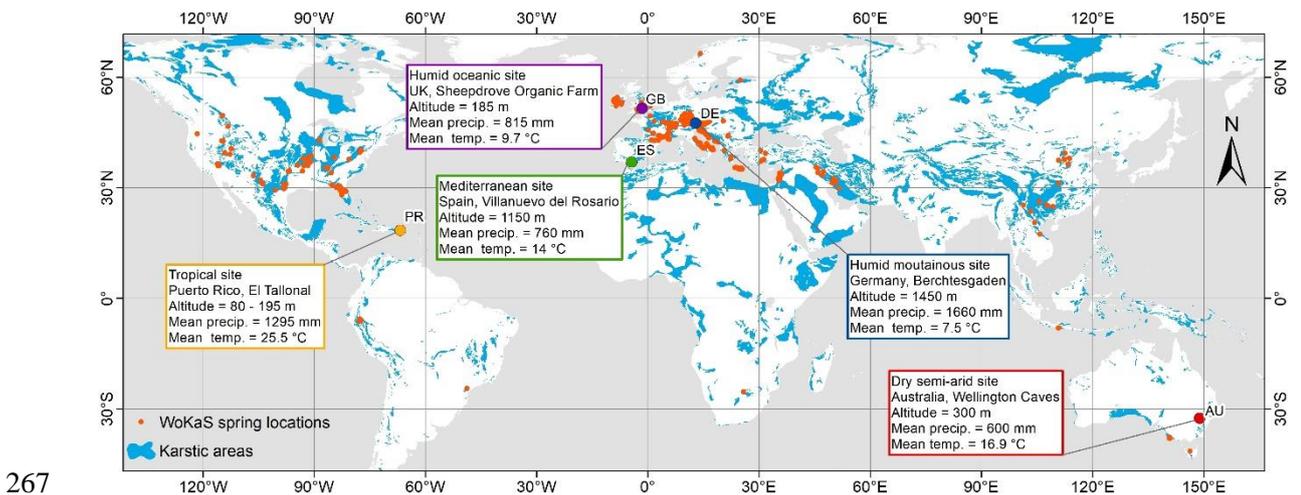
239 To evaluate the simulated soil storages of the global karst model with the observed soil
 240 moisture at our five sites, we compare monthly simulated soil saturation (averaged over the
 241 15 model compartments, Figure 3b) with the observations at three different depths
 242 individually to quantify the strength of their correlation. We derive the observed soil
 243 saturation as the ratio of observed water content over its maximum value of the entire
 244 monitoring period, as a proxy for effective porosity. For comparison with the model, we
 245 calculate the mean over all estimated soil saturation time series for the respective depth class
 246 (5cm, 10cm, or bottom). Since the simulated soil saturation represents the average over a 0.25
 247 $\times 0.25$ decimal degree grid and soil effective porosities may strongly vary across the sites,

248 different land covers and soil depths, a comparison of the absolute values of the simulated
249 and observed soil saturation remains limited. However, the correlation coefficient of the
250 observations and simulations has proven to be a good indicator to evaluate karst recharge
251 model performance in terms of observed and simulated soil moisture dynamics (Hartmann et
252 al. 2015; Sarrazin et al. 2018).

253 To evaluate the simulated recharge of the global karst model, we compare monthly simulated
254 recharge volumes with mean monthly observed spring discharges of the WoKaS database
255 (Olarinoye et al. 2020, described above). To minimize the effect of the insufficient length of
256 monthly spring discharge on the correlation, we only perform our correlation analysis for the
257 springs that have at least twelve of monthly discharge values (in total 305 springs). To account
258 for the delay produced by storage and lateral transmission in the phreatic zone, we use the
259 maximum correlation coefficient of a cross correlation analysis allowing up to three months
260 of delay of the observed discharge signal compared to simulated recharge. We assume that
261 the longer the time delay to the maximum r , the stronger the influence of the phreatic zone.

262 3. Results

263 Over 18 months of soil moisture were recorded at our sites by our global monitoring program
264 and >400 time series of karst spring discharges were collected for our global karst spring
265 hydrograph database (Figure 4). A 27-year long record of monthly karstic recharge
266 simulations was produced by our preliminary global model.



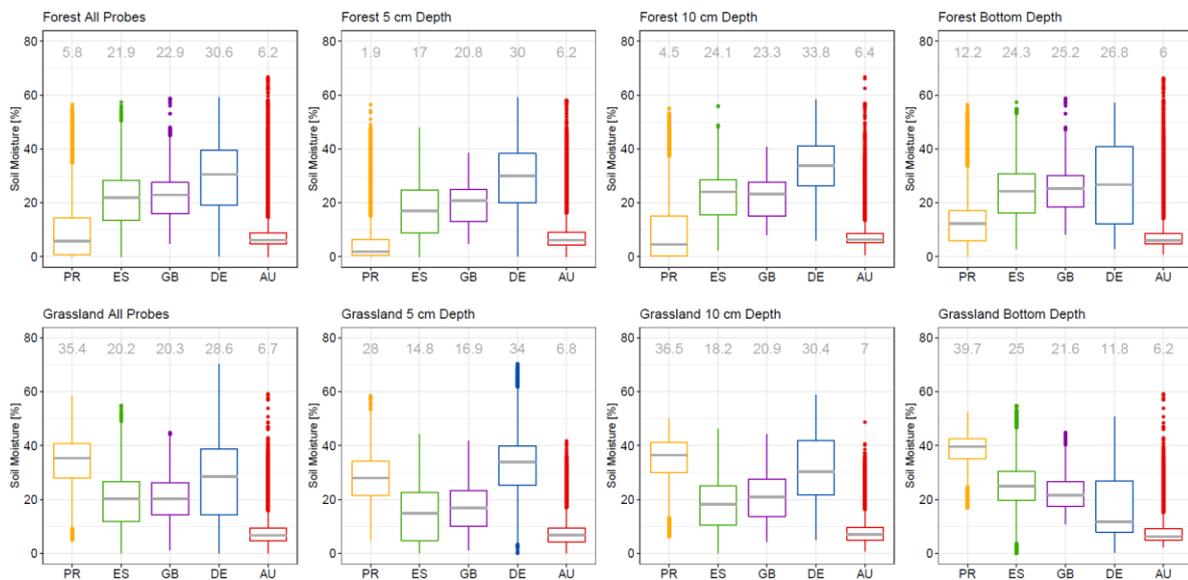
268 **Figure 4: Location of soil moisture monitoring plots and collected karst spring hydrographs (combined and adapted**
269 **from Berthelin et al. 2020; Olarinoye et al. 2020) over the karst regions of the world (Chen et al. 2017; Goldscheider**
270 **et al. 2020)**

271 3.1. Soil moisture observations at the grassland and forest sites

272 Starting between April and August 2018, all sites already collected more than 1.5 years of
273 soil moisture observations. Depending on the site location and the land cover type, they show

274 different patterns in their variability (Figure 5). The observations at the Puerto Rican site show
 275 the highest values of soil moisture at the grassland compared to all other sites. However, it is
 276 also the site with the lowest soil moisture values at the forest, almost similar to the Australian
 277 site. The soil moisture is increasing with depth at both vegetation type plots. In particular, at
 278 the lowest depth of the forest plot (5cm), the values of soil moisture are lower in comparison
 279 to the Australian site. On the other hand, the deepest probes show values two times higher
 280 than the deepest probes in Australia. Considering all depths together, the Australian site shows
 281 the lowest soil moisture values without significant differences between grassland and forest.
 282 The same is true when considering the soil moisture variations over different depths.

283 The soil moisture variability at the Spanish site is similar to the UK site, however with lower
 284 minimum values. The forest and grassland plot are not showing significant differences in
 285 general and for all depths considered separately. At the Spanish site, soil moisture tends to
 286 increase with depth, which is most visible at the grassland plot. At the forest plot, a decrease
 287 of average soil moisture is only from 5 to 10 cm, while the soil moisture variability of the 10
 288 cm and the bottom depth probes are very similar. At the UK site, the soil moisture is
 289 increasing with depth at both sites. The German site shows the highest soil moisture values
 290 after the Puerto Rican grassland plot. At the forest, soil moisture values are increasing
 291 between the 5 and 10 cm depth and decreasing between 10 cm and the bottom. At the
 292 grassland, the soil moisture values are decreasing continuously from the surface to the bottom.
 293 At both the German grassland and the forest, the deepest probes show the largest spread in
 294 their soil moisture dynamics.



295
 296 **Figure 5: Variability of observed soil moisture at the different sites for forest and grassland, for all depths together**
 297 **and for the three different depths separately (the bottom depth is defined as the depths where soil meets the epikarst,**
 298 **which varies between 20 and 80 cm among all our profiles)**

3.2. Collected karst spring hydrographs data

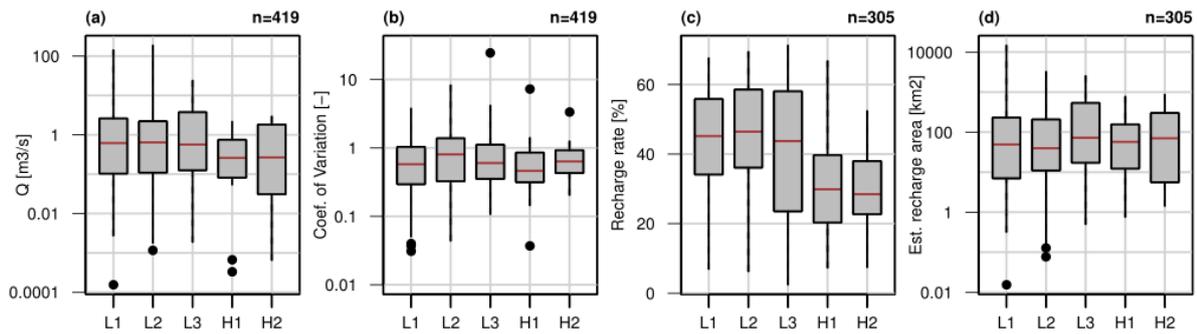
Through the established data collection framework and a combined community-effort, the WoKaS database presently archives more than 400 karst spring discharge observations globally (Olarinoye et al. 2020). The length of the datasets ranges from a few months up to 120 years with a median record length of 14 years (Table 2). 50% of the datasets contain discharge records sampled at a daily or sub-daily frequency but datasets in upper quartile have an observation temporal resolution of 4 days and above, most of which are datasets with longer data records. On average, 95% of the datasets in the WoKaS database provide continuous discharge records.

Table 2: Attributes of datasets from the WoKaS database

	Time span (years)	Temporal resolution (days)	Completeness (%)
1 st quartile	4	1	100
Median	14	1	100
3 rd quartile	29	4	100

The average discharge of collected karst springs for the five elevation classes spreads across 10^{-4} to 10^2 orders of magnitude (Figure 6). Larger springs are located at lower altitudes up to 1200 m. (elevation class L1, L2 and L3). Most springs located at higher elevations (< 1200 m, H1 and H2) have lower discharges. Springs located at lower elevations (L1, L2 and L3) show higher CVs compared to those located at higher elevations (H1 and H2) with less variability among different springs. From the recharge model described in subsection 2.3 we obtained recharge values from approximately 300 spring locations. Therefore, the recharge rate and recharge area analyses (Figure 6c and Figure 6d) are provided for the subset of WoKaS datasets for which recharge values have been estimated. The recharge rates range from low to very high values. We found a systematic pattern between recharge rates and altitude. High recharge rates of up to 70% are observed among L1, L2 and L3 springs (Figure 6c). 50% of the low-elevation springs (L1-L3) have a recharge rate higher than 45%, while the high-elevation springs (H1-H2) within the same quartile have recharge rates >30%. Irrespective of the elevation, the estimated values show a high variability in the recharge rates. In Figure 6d extreme ranges of recharge areas from values <1 km² to larger areas of up to 10⁴ km² are shown. Unlike for the recharge rates, there is no systematic pattern or order found between the recharge area and altitude. However, all spring classes have an almost similar range of median values which is slightly less than 100 km² recharge area. About a quarter or slightly more of the recharge areas at all classes are <10 km², and at least the upper quartile

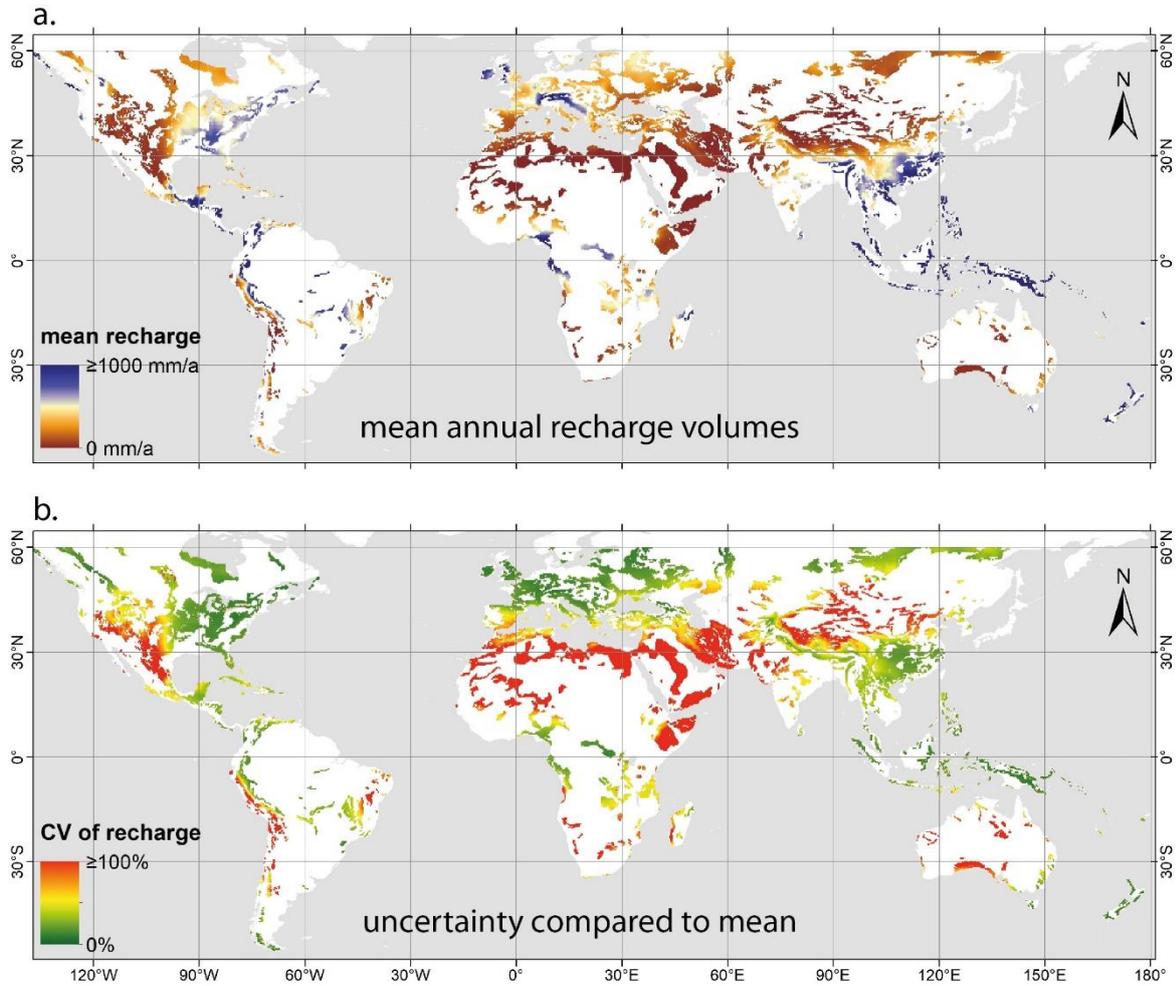
328 or even more have areas >100 km².



329
330 **Figure 6: (a) Distribution of average spring discharges, (b) their coefficients of variation, (c) their recharge rates, and**
331 **(d) estimated recharge areas over different altitude classes. Note the natural-logarithmic scale of the vertical axis for**
332 **discharge Q, coefficient of variation CV, and the estimated recharge areas (a), (b) and (d), respectively. L1, L2, L3,**
333 **H1 and H2 are spring elevation classes with the ranges L1≤400m, 400m<L2≤800m, 800<L3≤1200m,**
334 **1200m<H1≤1600m, and H2>1600m, respectively.**

335 3.3.Global groundwater recharge simulations

336 The mean annual recharge volumes derived for the period 1992 to 2019 resemble the meteoric
337 water availability in the different regions in the world (Figure 7a). Rainy regions such as
338 Scotland and Ireland, coastal regions and monsoonal regions are also characterized by
339 recharge volumes close to 1000 mm/a or more. On the other hand, regions that are
340 characterized by aridity show average recharge volumes as low as just few mm per year such
341 as in Northern Africa, Central Northern America, the Middle East or the Himalaya. In the
342 same regions, model uncertainty tends to larger values, with standard deviations as large or
343 even larger than the average annual recharge (Figure 7b), while uncertainty remains low in
344 the wetter regions.

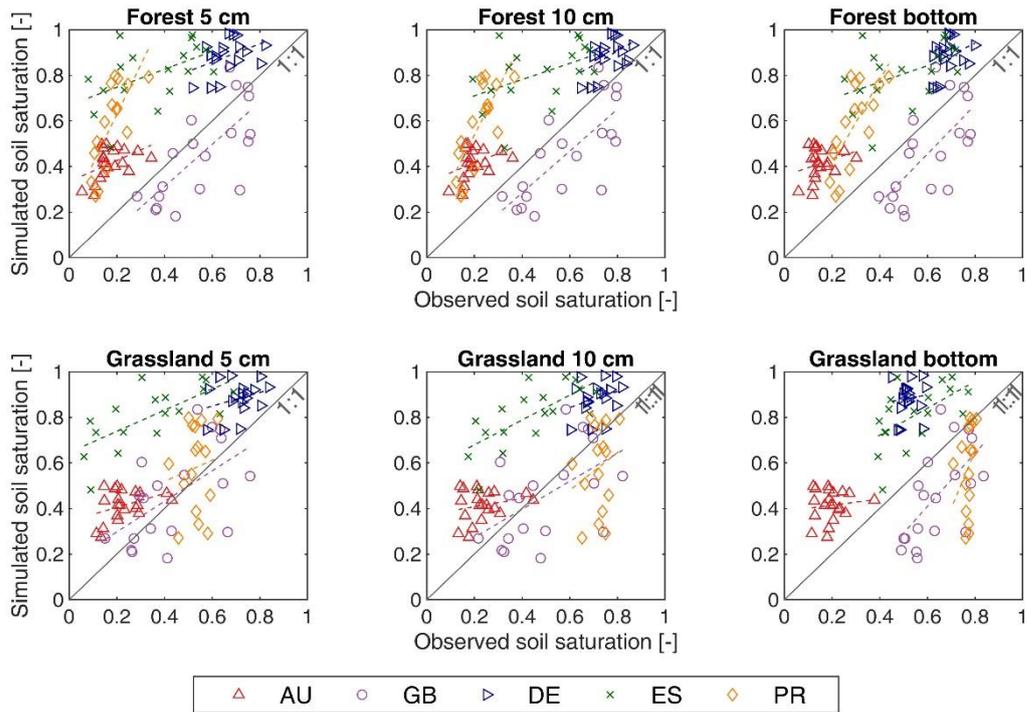


345
346 **Figure 7: (a) Mean annual recharge volumes and (b) their uncertainty expressed by the coefficient of variation CV**
347 **obtained by the preliminary un-calibrated model.**

348 **3.4.Evaluation of the global model with the soil moisture and spring** 349 **discharge observations**

350 We compare the simulations of soil saturation of the global karst recharge model with the
351 observed soil moisture dynamics at our five sites. At its present state, the model tends to over-
352 estimate the monthly average soil saturation at Austrian, German and Spanish sites regardless
353 of the land types (Figure 8). For Puerto Rico, the soil saturation of grassland is over-estimated,
354 as well. Generally, we see linear relationships with varying slopes between observed and
355 simulated monthly average soil saturation for forest and grassland and different depths, but
356 the strength of the linear correlation differs significantly among them (Table 3). In addition,
357 soil saturation shows different variability. Especially at Puerto Rico, it spreads in different
358 soil saturation ranges with forest <0.4 and grassland between 0.4 and 0.8 (Figure 8).

359



360
 361 **Figure 8: Comparisons between the monthly observed and monthly simulated soil saturation at three depths for two**
 362 **land types. The observed soil saturation is derived as the ratio of the soil moisture over the maximum value. Here the**
 363 **observed soil saturation at each depth represents the mean of all the measurements of 7–15 probes. The dashed lines**
 364 **show the linear regressions (no interception)**

365 Overall, the correlation coefficients r of the monthly observed and simulated soil saturation
 366 reach values up to 0.76. Weak relationships, $r < 0.45$, go along with insignificant correlation
 367 (Table 3). Forest and grassland show different strength of correlation, with stronger
 368 correlation for the forest than the grassland (except for the Spanish site).

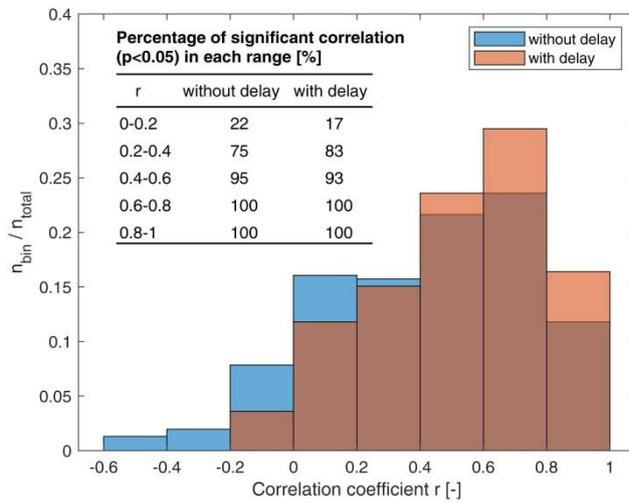
369 **Table 3 Correlation coefficients (r) between the monthly simulated and monthly observed soil saturation at three**
 370 **depths of the five sites**

Land type	Depth	AU	GB	DE	ES	PR
Forest	5 cm	0.46	0.73	0.42	0.52	0.74
	10 cm	0.38	0.75	0.49	0.46	0.76
	Bottom	0.29	0.66	0.33	0.45	0.72
Grassland	5 cm	0.38	0.57	0.29	0.70	0.13
	10 cm	0.22	0.53	0.29	0.70	0.21
	Bottom	0.12	0.62	0.10	0.57	0.30

371 note: the significance level for the non-marked values: $p < 0.05$, while for the other marked
 372 with grey background: $p > 0.05$.

373 The correlations between the monthly observed karst spring discharge and the corresponding
 374 monthly simulated recharge (Figure 9) show that 47% and 59% of the springs show a
 375 correlation coefficients $r \geq 0.5$ without and with consideration of time the delay from recharge
 376 to discharge, respectively. The larger the value of r , the more significant the correlation is
 377 observed. As expected, the correlation between recharge and discharge can represent how
 378 strong the recharge is linked to the discharge. We also see that the time delay from recharge

379 to discharge helps to obtain a better correlation for some regions (Figure 9). Few negative
 380 correlations between recharge and discharge suggest that local conditions of springs, e.g. the
 381 topography, could substantially affect this relationship



382
 383 **Figure 9: Distributions of the correlation coefficients r between the monthly simulated recharge and monthly**
 384 **observed karst spring discharge (from WoKas, Olarinoye et al. 2020). Blue and orange bars represent the correlation**
 385 **without and with time delay from recharge to discharge, respectively.**

386 4. Discussion

387 4.1.A better characterization of karstic recharge processes by soil 388 moisture dynamics

389 The dynamics of the collected soil moisture observations allow for preliminary interpretation
 390 and new region-specific and land use-specific insights (Figure 5). We find a strong linkage of
 391 climate and soil moisture. For instance, the highest soil moisture values occur at the site with
 392 a tropical climate at the grassland plot reflecting the wet tropical climate conditions. At the
 393 forest plot, rather low soil moisture values can be explained by the dense network of tree roots
 394 and few soil that can store the infiltrating water. High values of soil moisture are also
 395 measured at the German site, where high annual volumes of precipitation prevail. On the other
 396 hand, the low soil moisture values measured at the Australian site are coherent with the semi-
 397 arid local climate conditions. Despite their different climatic regions, the Spanish site
 398 (Mediterranean climate) and the UK site (oceanic climate) show similar variability of
 399 observed soil moisture dynamics. This is probably due to their similar annual precipitation
 400 volumes of 760 mm/a and 815 mm/a for the Spanish and UK site, respectively, and to their
 401 mean annual temperatures of 14°C (ES) and 5.4-14°C (UK) yet occurring with different
 402 strength of seasonality (Berthelin et al. 2020b).

403 The control of climate on soil moisture dynamics, and vice-versa, is well-known (Seneviratne

404 et al. 2010) but in order to derive improved concepts of groundwater recharge processes from
405 soil moisture dynamics, more parameters have to be considered such as soil texture,
406 antecedent moisture conditions, vegetation, and the epikarst (e.g., Perrin et al. 2003; Heilman
407 et al. 2014; Fu et al. 2015; Martos-Rosillo et al. 2015). Comparing the evolution of soil
408 moisture with depth, the probes at 5 cm depth present the lowest values at every site, and soil
409 moisture is increasing with depth. This is most probably linked to evaporation processes that
410 have a stronger impact on shallow soil water storage (Martini et al. 2015; Sprenger et al.
411 2016). Only the German site presents soil moisture values that decrease with depth indicating
412 rapid shallow subsurface flow paths (Chiffard et al. 2019), which may be favored by the
413 strong slopes of this site and its location in the mountains.

414 Yet, our comparison between sites, different soil depths and land cover types remains
415 qualitative and preliminary. The three main parameters explored above (climate, land cover
416 and depth) are not the only ones that influence soil moisture dynamics. In addition, the climate
417 could affect soil moisture dynamics differently in different seasons (Berthelin et al. 2020b)
418 and might be dependent on precipitation amount and intensities, too. The influence of
419 antecedent soil moisture conditions on recharge initiation could be revealed by considering a
420 larger number of extracted soil moisture events and their pre-event soil storages (Demand et
421 al. 2019). At those sites, where observations of groundwater, or of related fluxes like stream,
422 discharge, spring discharge or drip in caves are available, methods to estimate recharge from
423 soil moisture observations by simple models (Baker et al. 2020) or data-driven approaches
424 can be explored (Arnold et al. 2020). Those approaches may be supported by analysis of
425 stable isotopes in soil water as already proven to be useful in non-karstic settings by Sprenger
426 et al. (2015). Overall, with another 18-24 months of monitoring at our five sites, we are
427 confident that we can provide a dataset to advance the conceptual understanding of karstic
428 recharge and evapotranspiration processed both qualitatively and quantitatively.

429 **4.2. Pathways to upscale local understanding by the WoKaS database**

430 The WoKaS database tends to contain larger springs located at lower altitudes (Figure 6).
431 Hydrologically, springs at lower altitudes are located at or close to catchment outlet.
432 Therefore they drain a larger catchment area producing the large discharge volumes (Kresic
433 and Stevanovic 2009). Similarly, a higher and wider range of CV values is associated with
434 spring discharges at lower altitudes. This implies that springs at higher altitude have more
435 consistent discharge variability throughout the data record period, which may be due to the
436 seasonality produced by snow accumulation and snow melt (Chen et al. 2018). Since springs
437 at lower altitude drain a larger catchment area, the recharge area is consequently large with

438 variable recharge sources. This and other climate variables could be attributed to the higher
439 discharge variability of springs at lower elevation.

440 The high recharge rates up to 70% found at WoKaS springs' locations is no surprise.
441 Groundwater recharge is known to be higher in karst areas compared to other landscapes
442 (Hartmann et al. 2017) where more large fractions of the total precipitation volume can
443 infiltrate into groundwater (Bonacci 2001; Fiorillo et al. 2015). Usually, higher altitudes
444 receive more precipitation and higher recharge rates would be expected as well. This was
445 found, e.g., in the Swiss Alps by Malard et al. (2016) or the Italian Apennines by Allocca et
446 al. (2014). However, an increase of recharge rates with altitudes does not occur in our global
447 dataset as it also covers mountain ranges in very dry climate regions such as Central Northern
448 America, the Middle East and Southern Australia (Figure 7a). Considering the range of the
449 corresponding recharge areas (obtained by water balance, see section 2.2), we find similar
450 variability and averages for all altitudes, indicating that the dataset is not biased towards
451 different scales of karst systems at different altitudes.

452 The present analysis only gives an overview of the attributes and characteristics of karst
453 springs by exploring the collected datasets. The database still provides lots of potentials yet
454 to be explored. In future analysis, we will explore the dynamics of karst springs in different
455 regions to see how local factors influence discharge and recharge variability. The expected
456 outcome of this analysis will enable us to identify important local drivers and even predict
457 spring behavior in regions with non-reliable or no observation records. Also, the estimated
458 recharge areas could be a first step for their spatially explicit delineation (Malard et al. 2015).
459 As springs also reflect the dynamic behavior of karst aquifers, important information such as
460 recession parameters derived from the large datasets could be used to infer the dominance of
461 conduit and matrix contributions in different regions. Presently, the WoKaS datasets is
462 available in a stationary repository Efforts will be made to provide the datasets directly
463 through a web platform. Such development will allow for continuous growing of the database,
464 adding other complementing datasets and a web tool for instant analysis.

465 **4.3. Model deficiencies revealed by evaluation with the newly collected** 466 **observations**

467 The simulated mean annual recharge volumes mostly reflect the regional climatic conditions
468 (Figure 7a), a result which is very similar to its previous continental-scale application over
469 Europe Northern Africa and the Middle East (Hartmann et al. 2015). Small differences in
470 simulated average recharge volumes are most probably due to a new delineation of karst areas

471 (global model: WOKAM, Chen et al. 2017; continental model: Global distribution of
472 carbonate rocks, Williams and Ford 2006) and different simulated time periods (global model:
473 1992-2019; continental model: 2002-2012). However, when looking at the simulation
474 uncertainties (Figure 7b), the preliminary character of the global model is more obvious.
475 Especially in arid regions, the simulation uncertainty exceeds 100% making simulations of
476 karstic groundwater recharge basically useless for water management in those regions. Yet,
477 simulation uncertainty strongly reduces in semi-arid wetter regions where even these
478 preliminary simulations could be useful for water managers and water governance. In those
479 regions, the fractions of precipitation turned into recharge are substantially higher compared
480 to arid regions making precipitation itself a good predictor of groundwater recharge and
481 reducing the relative impact of the uncertain preliminary model on the mean annual recharge
482 estimates.

483 Through the comparison between observed and simulated soil saturation (Figure 8), we see
484 an obvious deviation of simulations of the global model and the observations, mostly
485 expressed through an over-estimation of soil saturation by the model. This deviation is
486 influenced by several aspects. The simulated soil saturation is averaged over a large grid that
487 represents the integral response for this large area, while the observed soil saturation is
488 measured at a specific point that can differ a lot because of heterogeneities of soil properties
489 and land cover from site to site, i.e., there is a problem of incommensurability (Beven 2018).
490 Considering the coefficient of correlation between simulations and observations as a measure
491 of model performance (similar to Hartmann et al. 2015; Sarrazin et al. 2018), we partially
492 circumvent this problem as r is not affected by differences of effective porosities. Comparing
493 the coefficients of correlation for the different sites and different land cover types (Table 3),
494 we clearly see that the model performs well for the UK forest and grassland sites, the Puerto
495 Rican forest site and the Spanish grassland site. Bad correlations that are sometimes both even
496 significant, are found at the Australian and German sites for both land covers, and the Puerto
497 Rican grassland. The different performances between grassland and forest point towards the
498 very simplified representation of land cover in our preliminary model (Sarrazin et al. 2018).
499 While the weak performance at the German site, which is located at ~1,450 m above sea level,
500 is most probably due the neglecting of snow processes in the model, the model deficiencies
501 at the Austrian site could be due to general uncertainty of the gridded input data for this region
502 as already discussed by Baker et al. (2020).

503 Considering the correlation between simulated monthly recharge and observed WoKaS spring
504 discharge, we find a large number of relatively high r values, despite of the preliminary state

505 of the model (Figure 9). But there is also a substantial number of springs with weak linear
506 relationships and even negative correlations between simulated recharge and observed
507 discharge. This could be explained by the limited consideration of the location and size of the
508 recharge area in the model. Since we cannot delineate the real recharge area of every spring,
509 we used the simulated recharge of the grid cell where the spring is located as the recharge of
510 this spring. However, the recharge area range across several grid cells, which may differ
511 strongly from its topographic area (Le Moine et al. 2007; Longenecker et al. 2017; Le Mesnil
512 et al. 2020). Due to this difference, the correlation for these springs can be biased. Another,
513 even more probable reason for the weak correlations is the lack of groundwater processes in
514 the preliminary model. This is confirmed by the improved correlations between recharge and
515 discharge that we obtain after allowing for the time delay from recharge to discharge.

516 **4.4. Towards reliable simulations for (inter)national water governance in** 517 **karst regions**

518 Our comparison of simulated and observed soil moisture clearly indicates that land cover has
519 significant influence on soil moisture as well as evapotranspiration mentioned above. Land
520 cover affects the partitioning of precipitation into evapotranspiration, soil moisture, and
521 surface runoff. This highlights the importance of including explicit land use types to improve
522 global karst recharge modelling, allowing to investigate impacts of land use change on the
523 recharge and discharge (Sarrazin et al. 2018). The poor performance at our mountain site in
524 Germany shows the need to add a snow model in order to include karst regions located in
525 mountain regions (Chen et al. 2018). More recent global input datasets such as MSWEP V2
526 (Beck et al. 2019) will help to improve the recharge simulations at dry sites such as our
527 Australian site. A need to include a karstic groundwater model is revealed through introducing
528 a time delay between recharge and discharge (Figure 9). The improved correlation between
529 simulated recharge and observed discharge after introducing such delay suggests that, despite
530 of the fast karstic flow paths, also slow groundwater transmission and storage takes place in
531 the phreatic zone. Adding a groundwater routine that considers system properties, such as the
532 distribution of the conduit networks, and the permeability of the matrix, will provide a better
533 representation of the delayed response of karst springs to a recharge signal (Geyer et al. 2008;
534 Covington et al. 2009)

535 The recharge area of karst aquifers is the most common spatial unit to investigate and model
536 karst springs. However, larger river basins that drain karst regions are often partially covered
537 by non-karstic areas. Water management at these basins therefore needs to understand the
538 combined behavior of both systems. Only few studies (e.g., Rimmer and Salingar 2006; Chen

539 et al. 2018) have considered both karstic and non-karstic components in catchment-scale
540 modeling. Challenges remain for modeling such systems, such as inter-catchment
541 groundwater flow can cross the topographic boundary of a catchment and result in unclosed
542 water balances (Le Mesnil et al. 2020). Neglecting this disagreement of surface and
543 subsurface catchments will limit the representation of karstic and non-karstic hydrologic
544 processes in combined modelling systems. Therefore, identification and quantification of
545 inter-catchment groundwater flow is of great importance. This may be achieved by diagnostic
546 signatures based on independent datasets and water balance (e.g., Liu et al. 2020) and new
547 approaches to integrate this information into regional models with combined karstic and non-
548 karstic processes representations.

549 **5. Conclusions**

550 This paper showed the most recent advances in developing a global karst modeling system
551 using a global soil moisture monitoring program and a global database of karst spring
552 hydrographs. Comparing the simulations of a preliminary version of the first global karst
553 recharge model with the soil moisture observations reveals that improvements of the soil and
554 epikarst processed in the model are still necessary to obtain a better representation of different
555 land cover types and snow processes. The comparison of observed spring discharge with the
556 simulated recharge values strongly points towards the need to incorporate groundwater
557 dynamics including the interplay of partially overlapping surface and subsurface catchments
558 and the influence of non-karstic units in karst dominated river basins. Consequently, the
559 comparison of the preliminary model with the newly collected soil moisture data and spring
560 discharge observations provides detailed and explicit directions to make important
561 advancements towards the first global karst simulation model. Such modeling system will not
562 only provide information about water availability in the simulated catchments. Karst aquifers
563 provide drinking water for a large part of the world population (Ford and Williams 2013) and
564 are among those groundwater resources that are far from being over-exploited (Stevanović
565 2019). Applied at a global scale and fed by climate projections, the model will also allow to
566 identify hot spots of current or future water scarcity in the karst regions around the globe and
567 where karst aquifers may mitigate water shortages. That way, it can support national to
568 international water governance to develop regional and local mitigation measures to
569 successfully tackle the impacts of climate change, land use a change and population growth.

570

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572 The global karst spring hydrographs dataset (WoKaS) is freely downloadable from
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574 [_management_of_the_world_s_fastest-flowing_groundwater/9638939/2](https://figshare.com/articles/World_Karst_Spring_hydrograph_WoKaS_database_for_research_and_management_of_the_world_s_fastest-flowing_groundwater/9638939/2). The code of the preliminary
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584

585 **Author contributions**

586 AH conceptualized the paper, developed and applied the global recharge model, compiled the
587 individual contributions the coauthors and wrote Introduction, the methods, results and discussion part
588 of the global recharge model and Conclusions. YL prepared, analyzed, visualized and interpreted the
589 methods, results and discussion part of the comparison of the global recharge model and the newly
590 obtained soil moisture and spring discharge observations. TO prepared, analyzed, visualized and
591 interpreted the methods, results and discussion part of the global karst spring hydrograph database.
592 RB prepared, analyzed, visualized and interpreted the methods, results and discussion part of the
593 global soil moisture monitoring program. VM analyzed and visualized the results of the global
594 recharge model, and reviewed and edited the final version of the manuscript.

595

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