

Groundwater representation in continental to global hydrologic models: a call for open and holistic evaluation, conceptualization and classification

This is a non-peer reviewed preprint submitted to EarthArXiv which currently in review with *Water Resources Research*

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37 **Key points**

- 38 • As groundwater is increasingly being included in large-scale models, we seek to improve transparency
39 in model formulation and evaluation
- 40 • Integration of data-, model-, and expert-driven model evaluation approaches can reduce evaluation
41 limitations due to data scarcity
- 42 • Holistic evaluation, transparent conceptualization and systematic classification may significantly
43 improve groundwater representation in large-scale models

44 **Abstract**

45 Continental- to global-scale hydrologic models increasingly include representations of the Earth's
46 groundwater system. A key question is how to evaluate the realism and performance quality of such
47 large-scale groundwater models given limitations in data availability. We argue for a transparent
48 approach to system conceptualization, which would enable distinguishing differences in model behavior
49 that are caused by system conceptualization from those that are caused by differences in the
50 implementation of physical processes in models. In addition, we argue for systematic model
51 classification to distinguish the impacts of choices in model implementation. Evaluation options include
52 comparing model outputs with available observations of groundwater levels or other state or flux
53 variables (data-driven evaluation); comparing several models with each other with or without reference
54 to actual observations (model-driven evaluation); or relying on experts to propose hydrologic behaviors
55 that we expect to see in particular regions or at particular times (expert-driven evaluation). We discuss
56 the strengths and weaknesses of these three evaluation strategies as well as how they might be
57 integrated to achieve a more holistic approach. We call on various scientific communities to join us in
58 our effort to improve the representation of groundwater in continental to global models using the
59 recommendations discussed here.

60 **Plain language summary**

61 Groundwater is increasingly being included in large-scale (continental to global) land surface and
62 hydrologic simulations. However, it is challenging to evaluate these simulations because groundwater is
63 “hidden” underground and thus hard to measure. Here, we make recommendations to improve the
64 incorporation of groundwater in large-scale models. These include: more clearly describing our mental
65 models of how groundwater flows and interacts with other processes (‘model conceptualization’);
66 classifying different approaches to including groundwater in models, and choosing an approach based
67 on its suitability to the goals of a study (‘model classification’); and using multiple complementary
68 strategies to assess the performance of a model (‘model evaluation’). As large-scale land surface and
69 hydrologic models “move down” into the subsurface, modeling strategies from the hydrogeology
70 community need to “move up” towards the surface and be combined with improved model evaluation
71 strategies.

72 **WHY AND HOW MODEL GROUNDWATER AT CONTINENTAL TO GLOBAL SCALES?**

73 Groundwater is the largest human- and ecosystem-accessible freshwater storage component of the
74 hydrologic cycle (Gleeson et al., 2016; UNESCO, 1978). Therefore, better understanding of groundwater
75 dynamics is critical at a time when the ‘great acceleration’ (Steffen et al., 2015) of many human-induced
76 processes is increasing stress on water resources (Wagner et al., 2010), especially in regions with
77 limited data availability and analytical capacity. We urgently require predictive understanding about
78 how groundwater, used by humans and connected with other components of the Earth System,
79 operates at a variety of scales. The goals of representing groundwater in continental to global models
80 include:

- 81 (1) Understanding and quantifying interactions between groundwater and past, present and future
82 climate. Groundwater systems can have far-reaching effects on climate affecting modulation of

83 surface energy and water partitioning with a long-term memory (Anyah et al., 2008; Maxwell and
84 Kollet, 2008; Krakauer et al., 2014; Maxwell et al., 2016; Taylor, et al., 2013; Meixner et et, 2018;
85 Wang et al., 2018; Keune et al., 2018). For example, while there have been significant advances in
86 understanding the role of lateral groundwater flow on evapotranspiration (Maxwell & Condon,
87 2016; Bresciani et al, 2016), the broader time and space scales of the interactions between climate
88 and groundwater remain incompletely resolved (Cuthbert et al., 2019).

89 (2) Understanding and quantifying two-way interactions between groundwater and the rest of the
90 hydrologic cycle, as well as the broader Earth System. As the main storage component of the
91 freshwater hydrologic cycle, groundwater systems impact the sea level (Döll et al., 2014; Wada,
92 2016; Wada et al. 2016); freshwater and solute inputs to the ocean (Moore, 2010; Sawyer et al.,
93 2016); agricultural productivity and other ecosystem services in both irrigated and rainfed systems
94 (Scanlon et al., 2012; Qiu et al., 2019; Visser, 1959; Zipper et al., 2015, 2017); and streamflows and
95 groundwater-dependent ecosystems (Batelaan et al., 2003; Boulton & Hancock, 2006; Kløve et al.,
96 2011).

97 (3) Informing water decisions and policy for large, and often transboundary, groundwater systems in
98 an increasingly globalized world (Wada & Heinrich, 2013). For example, global trade in virtual
99 water causing aquifer stress in disparate regions (Dalin et al., 2017) shows the value of large-scale
100 models in groundwater policy. Another example is sub-Saharan Africa, where groundwater
101 recharge from large-scale models has been used to quantify groundwater resources, even though
102 large-scale models do not yet include all recharge processes that are important in this region
103 (Taylor et al., 2013).

104 (4) Offering the opportunity to create visualizations and interactive opportunities that engender local
105 and global populations to understand and appreciate what is happening in the large time and
106 space scales of environmental systems.

107 In sum, continental- to global-scale hydrologic models incorporating groundwater offer a coherent
108 scientific framework to examine the dynamic interactions between the Earth System above and below
109 the land surface, and are compelling tools for conveying the opportunities and limits of water resources
110 to people so that they can better manage the regions they live in, and better understand the world
111 around them.

112

113 Numerous land surface models, global hydrological and water resource models, and Earth System
114 models (herein we refer to all these types of continental to global models as ‘large-scale models’) have
115 incorporated or intend to incorporate groundwater to varying levels of complexity depending on the
116 model provenance, users, and purposes. Historically, large-scale hydrological models were intended for
117 simulating streamflow, with groundwater only included to define baseflow or for its influence on land
118 surface processes, like evapotranspiration and runoff production, via soil moisture / groundwater fluxes.
119 As a result, groundwater was not explicitly represented or represented in simple ways such that lateral
120 subsurface flow only occurs to the draining river in each grid cell, and it is often described by a linear
121 reservoir (Alcamo et al., 2003; Gascoin et al., 2009; Ngo-Duc et al., 2007), or using subgrid scale
122 approaches based on the topographic index (Famiglietti & Wood, 1994; Koster et al., 2000; Niu et al.,
123 2003; Takata et al 2003.). More recently, more rigorous approaches have been developed to explicitly
124 simulate lateral groundwater flows between all model grid cells or elements for large-scale models (Fan
125 et al, 2013; Lemieux et al 2008; de Graaf et al., 2017; Kollet et al., 2017; Maxwell et al., 2016; Reinecke
126 et al., 2018; Vergnes & Decharme, 2012). It is important to note that herein ‘large-scale models’ refer to
127 models that are laterally extensive across multiple regions (hundreds of kilometers), rather than specific
128 to regional aquifers and focus on the shallow subsurface (upper hundreds of meters). We acknowledge
129 and build upon well-established modeling strategies for regional aquifer systems (Anderson &
130 Woessner, 1992; Rossman & Zlotnik, 2013), deeper groundwater flow (Garven, 1995; Person et al.,

131 1996), regional groundwater flow (Tóth, 1963, Freeze and Witherspoon, 1966). The simulation of
132 groundwater in large-scale models is a nascent and rapidly developing field with significant
133 computational and parameterization challenges which has led to significant and important efforts to
134 develop and evaluate individual models. Now that a number of models are developed and developing, it
135 is equally important that we advance how we evaluate and test such models.

136

137 **The goal of this commentary is to advocate and provide recommendations for the transparent**
138 **conceptualization, systematic classification, and robust evaluation of the groundwater component of**
139 **large-scale models in order to improve the representation of groundwater, and thus promote better**
140 **understanding of global water science and sustainability.** We bring together somewhat disparate
141 scientific communities as a step towards greater community-level cooperation on these issues, including
142 global hydrology and land surface modelers, local to regional hydrogeologists, and hydrologists focused
143 on model development and evaluation. Our main focus is model evaluation because this is the heart of
144 model trust and reproducibility (Hutton et al., 2016). We start however with a discussion on model
145 conceptualization and classification which we believe are integral to the evaluation process as discussed
146 below. We develop a holistic framework for evaluating global groundwater models (that could be
147 extended to other elements of hydrological models) that includes and extends current efforts to
148 compare large-scale hydrologic models (Scanlon et al., 2018) or evaluate large-scale groundwater
149 models and schemes (e.g. Döll et al., 2014; Maxwell and Condon 2016; de Graaf et al., 2017; Koirala et
150 al., 2019). In each section we conclude with goals and possible actions meant to invigorate the scientific
151 community. Since groundwater is being integrated into a diverse range of models, we expect multiple
152 Earth Science communities to be interested and impacted by these tangible steps towards improved
153 representation of groundwater in large-scale models.

154 **SYSTEM CONCEPTUALIZATION**

155 Local to regional groundwater models conventionally start with clearly drawn and described conceptual
156 models, which are often seen as a hypothesis or a combination of hypotheses for the aspects of the
157 groundwater system that are relevant to the model objective (Enemark et al., 2019); this is such an
158 important part of local to regional groundwater models that it has been codified into standard practice
159 (e.g. ASTM standards). We define ‘conceptual models’ (following Anderson & Woessner, 1992; Enemark
160 et al., 2019) as pictorial, qualitative descriptions of the hydrologic system in terms of its salient
161 subsurface geometry and properties as well as surface water and land surface processes and geometry
162 (similar to perceptual models in hydrologic modeling; Beven, 2001). This type of conceptual model is
163 slightly different than other conceptual models representing hydrologic processes (e.g. Salvucci &
164 Entekhabi, 1995 Figure 4; Kollet & Maxwell, 2008 Figure 1; Fan, 2015 Figures 2 and 4, Sutanudjaja et al.,
165 2018 Figure 1) that generally do not include subsurface geometry and properties. It is important to
166 differentiate conceptual models from ‘computer models’ which are any analytical or numerical
167 procedures that simulate the behavior of an environmental system.

168

169 Conceptual models form the basis of computer models and allow for multiple, competing
170 conceptualizations and hypotheses, which is healthy for scientific progress (Enemark et al., 2019), and
171 valuable for communication within scientific circles and with stakeholders (Mahmoud et al., 2009).
172 However, conceptual models for large-scale models have generally not been published or received the
173 attention they deserve. Figure 1 is in fact one of these conceptual models, in the mind of one of the
174 developers of the global hydrologic model PCR-GLOBWB (M. Bierkens), but never before published. Not
175 publishing, discussing, or debating conceptual models impedes rapid and clear understanding of the
176 assumptions on which models rely, and does not communicate how the modeller sees the hydrologic
177 system under study.

178

179 Conceptual models likely have to differ between local- and large-scale models; at the local-scale actual
180 geology and surface water features can be included in a pictorial drawing of the model domain, which is
181 not (yet) possible in the conceptual models for large-scale computer models. We argue that conceptual
182 models are crucial for developing better computer models of groundwater systems, as well as for
183 presenting and deriving hypotheses that could be used in evaluation, as described below. In fact, the
184 hydrologic modelling community has argued for some time that consistency between the conceptual
185 model and the resulting expected behavior is at least as important as some optimal statistical fits to
186 observations (Wagener & Gupta, 2005; Hrachowitz et al., 2014). For the sake of brevity, drawing and
187 describing possible conceptual models for large-scale models is beyond the scope of this commentary
188 and will be the focus on a future related commentary. **We recommend that large-scale model**
189 **development always includes open and published conceptual models and descriptions that capture**
190 **the modelers' understanding of the hydrologic system, without being limited to the capabilities of**
191 **computer models.**

192 **MODEL CLASSIFICATION**

193 Computer models are used to translate qualitative conceptual models into quantitative information
194 about hydrologic systems. Various large-scale models exist along a spectrum of model complexity so it
195 can be difficult to determine the most appropriate model for a specific problem. To facilitate model
196 selection and comparison, we developed a simple but systematic classification for groundwater in large-
197 scale models (Table S1). We argue that groundwater in current large-scale models can be classified
198 functionally by two aspects that are crucial to how groundwater impacts water, energy, and nutrient
199 budgets. First, whether lateral subsurface flow is simulated to a river within a cell, as 2D lateral
200 groundwater flow between all cells or as 3D groundwater flow. Second, we distinguish two types of

201 coupling between groundwater and related compartments (variably saturated soil zone, surface water,
202 atmospheric processes in terrestrial and aquatic settings): ‘one-way’ coupling (recharge is imposed from
203 the surface, with no feedback from capillary rise; groundwater flow to the surface does not depend on
204 surface head) from ‘two-way’ coupling involves feedback loops. We also note atmospheric coupling
205 which involves coupling a groundwater-surface model with an atmospheric model, to propagate the
206 influence of groundwater from the surface to the atmosphere, and the resulting feedback onto the
207 surface and groundwater. This classification scheme (which could also be called a model typology) is
208 based on a number of model characteristics such as the fluxes, stores and other features (Table S1). We
209 suggest use of this process-based classification scheme rather than grouping models by model purpose
210 because many models are used for multiple purposes.

211

212 The spectrum of model complexity is significant, so an important question is ‘what level of complexity is
213 appropriate?’ This question depends primarily on the model purpose (i.e. the question to be answered),
214 the alignment of the computer model with the appropriate conceptual model, and the computer
215 model’s performance. All models have an inherent purpose (even if not clearly stated) and the principle
216 of parsimony suggests that models should only be as complex as appropriate for their purpose (Young et
217 al., 1996), though researcher and stakeholder familiarity with a model are also common and important
218 considerations (Addor & Melsen, 2019). For example, a model with no 2D lateral flow between cells may
219 be appropriate for the purpose of basin-scale water balance estimation in certain regions over large
220 time scales. But the same model would be clearly inappropriate for assessing the role of regional
221 groundwater flow because lateral flow between basins is not considered. **We thus recommend that the**
222 **purpose of any groundwater implementation in large-scale models should be clearly stated and**
223 **salient model characteristics are comprehensively considered and described (using Table S1 as a**
224 **guide).**

225 **MODEL EVALUATION**

226 We suggest that a holistic framework is needed for evaluating global groundwater models that requires
227 at least three dimensions (Figure 2): data-, model- and expert-based evaluation that are potentially
228 mutually beneficial because each strategy has strengths and weaknesses.

229

230 **Data-driven model evaluation** is the focus of most current efforts and is important because we want
231 models to be consistent with real-world observations, though what we mean by consistent might vary as
232 discussed below. Data-driven model evaluation could use data at site, basin/regional, and global scales,
233 and is thus dependent on the quality, distribution, and availability of data (Table 1). Unfortunately, there
234 are significant inherent challenges with regard to groundwater data because groundwater fluxes and
235 stores are largely unmeasurable: groundwater recharge is not directly measurable except for meter-
236 scale lysimeters (Scanlon et al., 2002); change in groundwater storage can be indirectly estimated from
237 satellite gravimetry (GRACE: Gravity Recovery And Climate Experiment) but only after model-based
238 subtraction of water storage changes in glaciers, snow, soil and surface water bodies (Lo et al., 2016;
239 Rodell et al., 2009; Wada, 2016); baseflow from groundwater to surface water bodies is only derived
240 using a baseflow separation algorithms or tracers (Genereux, 1998; Tallaksen, 1995) but this is only
241 possible if there are not significant surface water bodies upstream; and the groundwater contributions
242 to evapotranspiration in groundwater-dependent ecosystems can be estimated using water table
243 fluctuations (Loheide et al., 2005), but this is rarely done and also requires specific yield estimates which
244 are often highly uncertain. Even hydraulic head data from well observations, often considered the
245 crucial data for groundwater model evaluation, have limitations for use in large-scale model evaluation
246 such as (1) observational errors and uncertainty (Post and von Asmuth, 2013); (2) groundwater storage
247 variation can only be derived using estimated storage coefficients; (3) heads can reflect the poro-elastic
248 effects of mass loading and unloading rather than necessarily aquifer recharge and drainage (Burgess et

249 al, 2017); (4) heads can be directly used to evaluate models that compute head and not only storage
250 variations, and (5) even if models compute heads, there is a scale problem (point observation vs.
251 simulated grid cell average). To date, models have been compared to observed heads rather than
252 depths to water table, which would show greater discrepancy but are more meaningful descriptors of
253 system dynamics. For all data, there is a significant commensurability problem (scale difference between
254 observation and modelled variable or state) (Beven and Cloke, 2012). In sum, much of the data
255 sometimes called ‘observations’ are modeled or derived quantities, and often at the wrong scale for
256 evaluating large-scale models, which means modelers have to ask themselves what level of agreement is
257 reasonable to aim for given these data limitations.

258

259 Despite these challenges, we foresee significant opportunities for data-driven model evaluation and do
260 not see data availability as a reason to exclude groundwater in Earth System models or to avoid
261 evaluating these models. So far, all efforts to our best knowledge have only used GRACE, hydraulic head
262 data, or baseflow (Lo et al., 2008; Döll et al., 2014; Maxwell and Condon, 2016; de Graaf et al., 2017;
263 Scanlon et al., 2018) but there are significant possibilities for new data sources (see Table 1 for
264 strengths, limitations and availability of each data source). Large-scale models could be more holistically
265 evaluated with existing data such as the spatial distribution of perennial streams and baseflow data. In
266 some cases, observed evapotranspiration from global networks (e.g., FLUXNET) and novel soil moisture
267 technologies (e.g., COSMOS; Rosolem et al., 2014) may also help to constrain groundwater recharge
268 estimates (Hartmann et al., 2015). We might also be able to utilize existing datasets in new ways; for
269 example, Hartmann et al. (2017) used recharge studies of 38 separate karst systems across Europe to
270 assess the variability of recharge modelled in their large-scale model across this domain. The use of
271 various datasets derived from or for large-scale models, such as evapotranspiration, vegetation indices
272 and surface water inundation, could be refined to evaluate groundwater models, as recently attempted

273 in the Ouémé basin (Benin) by Rashid et al. (2019) to evaluate three land surface models with
274 groundwater against multiple observations. Such datasets are not listed in Table 1 as methods to use
275 them globally have not yet been developed, but recent advances to constrain distributed estimations of
276 the global water cycle by Earth observation products including GRACE (Pan et al., 2012; Pellet et al.,
277 2019) are particularly promising. Some of them have also been explicitly compared with residence time
278 and tracer data (Maxwell et al., 2016) which have also been recently compiled globally (Gleeson et al.,
279 2016; Jasechko et al., 2017). This could be an important evaluation tool for large-scale models that are
280 capable of simulating flow paths, or can be modified to do so. In the future, additional new datasets
281 could be derived using meta-analysis and/or, geospatial analysis of gaining or losing stream reaches
282 (e.g., from interpolated head measurements close to the streams), springs and groundwater-dependent
283 surface water bodies, evapotranspiration from groundwater and piezometric lysimetry; each of these
284 new data sources could in principle be developed using methods already applied at regional-scales. **We**
285 **recommend evaluating models with a broader range of currently available data sources (with explicit**
286 **consideration of data uncertainty) while also simultaneously working to derive new data sets.**
287 However, data distribution and commensurability issues will likely still be present, which underscores
288 the importance of the two following strategies.

289
290 **Model-driven model evaluation** which includes model intercomparison projects (MIP) and model
291 sensitivity and uncertainty analysis can be done with or without explicitly using observed data for
292 comparison. The original MIP concept offers a framework to consistently evaluate and compare models,
293 and associated model input, structural, and parameter uncertainty under different objectives (e.g.,
294 climate change, model performance, human impacts and developments). Since the Project for the
295 Intercomparison of Land-Surface Parameterization Schemes (PILPS; Sellers et al., 1993), the first model
296 intercomparison project (MIP), LSM community has exploited MIPs to deepen understanding of land

297 physical processes and to improve their numerical implementations to be represented in various scales
298 from regional (e.g., Rhône-aggregation project; Boone et al., 2004) to global (e.g., Global Soil Wetness
299 Project; Dirmeyer, 2011). Two examples of recent model intercomparison efforts, including some
300 models of Table S1, illustrate the general MIP objectives and practice. First, ISIMIP (Schewe et al., 2014;
301 Warszawski et al., 2014) assessed water scarcity at different levels of global warming. Second, IH-MIP2
302 (Kollet et al., 2017) used both synthetic domains and an actual watershed to assess fully-integrated
303 hydrologic models because these cannot be validated easily by comparison with analytical solutions and
304 uncertainty remains in the attribution of hydrologic responses to model structural errors. Model
305 comparisons have revealed differences, but it is often unclear whether these stem from differences in
306 the model structures, differences in how the parameters were estimated, or from different other
307 modelling choices (Duan et al., 2006). Attempts for modular modelling frameworks to enable
308 comparisons (e.g. Clark et al., 2015) or at least shared explicit modelling protocols and boundary
309 conditions (Ceola et al., 2015; Warszawski et al., 2014) have been proposed to reduce these problems.
310 Inter-scale model comparison - for example, comparing a global model to a regional model - is a
311 potentially useful approach which is emerging for surface hydrology models (Hattermann et al., 2017;
312 Huang et al., 2017) and could be applied to large-scale groundwater models. Combining inter-model and
313 inter-scale comparisons could leverage the strengths of each of the methods. For example, attempts to
314 document and compare flow path and transit time distributions, currently limited to the small scale
315 (Thomas et al., 2016), could be extended to larger scales. Finally, we note that large-scale groundwater
316 models have only been assessed to a very limited degree with respect to understanding, quantifying,
317 and attributing relevant uncertainties. Expanding computing power, along with the improvement of
318 conceptualization and classification that we call for above, will all enable more robust sensitivity and
319 uncertainty analysis such as used in regional-scale groundwater models (Habets et al., 2013; Hill, 2006;
320 Hill & Tiedeman, 2007). For now, we suggest applying computationally frugal methods such as the

321 elementary effect test or local sensitivity analysis (Hill, 2006; Morris, 1991; Saltelli et al., 2000). Such
322 sensitivity and uncertainty analyses should be applied not only to model parameters and forcings but
323 also to model structural properties (e.g. boundary conditions, grid resolution, process simplification,
324 etc.) (Pianosi et al., 2016). **We thus recommend significant expansion of groundwater focused model**
325 **inter-comparison projects (both inter-model and inter-scale) as well as more sensitivity and**
326 **uncertainty analyses.**

327

328 A path much less traveled is **expert-driven model evaluation** which would develop hypotheses of
329 phenomena (and related behaviors or signatures) we expect to emerge from large-scale groundwater
330 systems based on our expert knowledge, intuition, or experience. The recent discussion by Fan et al.
331 (2019) shows how hypotheses about large-scale behavior might be derived from expert knowledge
332 gained from studying smaller scale systems such as critical zone observatories. Large-scale models could
333 then be evaluated against these hypotheses, providing a general opportunity to advance how we
334 connect hydrologic understanding with large-scale modeling - a strategy that could potentially reduce
335 epistemic uncertainty which may be especially useful for groundwater systems given the data limitations
336 described above. Choosing appropriate and effective hypotheses is crucial and should likely focus on
337 large-scale controlling factors or relationships between controlling factors and output in different parts
338 of the model domain; hypotheses that are too specific may only be able to be tested by certain model
339 complexities. To illustrate the type of hypotheses we are suggesting, we list some examples of
340 hypotheses drawn from current literature:

- 341 ● water table depth and lateral flow strongly affect transpiration partitioning (Famiglietti and
342 Wood, 1994; Salvucci and Entekhabi, 1995; Maxwell & Condon, 2016);
- 343 ● the percentage of inter-basinal regional groundwater flow increases with aridity or decreases in
344 frequency of perennial streams (Gleeson & Manning, 2008; Goderniaux et al, 2013); or

345 • human water use systematically redistributes water resources at the continental scale via non-
346 local atmospheric feedbacks (Al-Yaari et al., 2019; Keune et al., 2018).

347 Alternatively, hypotheses could be drawn from hydrologic intuition and form the basis of model
348 experiments, potentially including extreme model experiments (far from the natural conditions). For
349 example, an experiment that artificially lowers the water table by decreasing precipitation (or recharge
350 directly) could hypothesize that ‘the drainage flux will increase and evaporation flux will decrease as the
351 water table is lowered’. These hypotheses are meant only for illustrative purposes and we hope future
352 community debate will clarify the most appropriate and effective hypotheses. There is a close link
353 between this approach and the need for open system conceptualizations in which this knowledge could
354 be captured.

355
356 Moving such expert-driven approaches forward should include more formal approaches to elicit expert-
357 knowledge in a structured manner (Aspinall, 2010; Cooke, 1991), preferably including the uncertainty in
358 this knowledge. In the groundwater modelling community, the term *expert knowledge* is often used to
359 describe the constraints on parameter values that are provided prior to calibration or uncertainty
360 analysis (Ross et al., 2009; Doherty and Christensen, 2011; Brunner et al., 2012; Knowling and Werner,
361 2016; Rajabi and Ataie-Ashtiani, 2016). The term expert opinion is sometimes alternatively used (Ross et
362 al., 2009; Rajabi and Ataie-Ashtiani, 2016). The latter term may be preferable because it emphasizes a
363 preliminary state of knowledge (Krueger et al., 2012). Expert knowledge/opinion is also implicitly used at
364 higher levels when defining the model structure (i.e., all the way from conceptualization down to
365 mathematical solution) (Krueger et al., 2012; Rajabi et al., 2018).

366 Hence, it can be seen that expert knowledge/opinion is commonly used to directly inform the model
367 structure and parameters. In contrast, it seems that the use of expert knowledge/opinion about *system*
368 *behavior* is less common. Yet, it is intuitive that information about system behavior can help in

369 evaluating the plausibility of model outputs (and thus of the model itself). This is what we call expert-
370 driven evaluation herein. **We recommend the community uses expert elicitation to develop effective**
371 **hypotheses that directly link to the relevant large-scale hydrologic processes of interest.**

372

373 Ideally, all three strategies (data-driven, model-driven, expert-driven) should be pursued simultaneously
374 because the strengths of one strategy might further improve others. For example, expert- or model-
375 driven evaluation may highlight and motivate the need for new data in certain regions or at new
376 resolutions. Or data-driven model evaluation could highlight and motivate further model development
377 or lead to refined or additional hypotheses. **We thus recommend the community significantly**
378 **strengthens efforts to evaluate large-scale models using all three strategies.** Implementing these three
379 model evaluation strategies may require a significant effort from the scientific community, so we
380 therefore conclude with a perspective on how this might be achievable. For example, in ISIMIP
381 (Warszawski et al., 2014), modelling protocols have been developed with an international network of
382 climate-impact modellers across different sectors (e.g. water, agriculture, energy, forestry, marine
383 ecosystems) and spatial scales. Originally, ISIMIP started with multi-model comparison, i.e. **model-driven**
384 **model evaluation**, with a focus on understanding how model projections vary across different sectors
385 and different climate change scenarios (ISIMIP Fast Track). However, more rigorous model evaluation
386 came to attention more recently with ISIMIP2a, and various observation data, such as river discharge
387 (Global Runoff Data Center), terrestrial water storage (GRACE), and water use (national statistics), have
388 been used to evaluate historical model simulation (**data-driven model evaluation**). To better
389 understand model differences and to quantify the associated uncertainty sources, ISIMIP2b includes
390 evaluating scenarios (land use, groundwater use, human impacts, etc) and key assumptions (no explicit
391 groundwater representation, groundwater availability for the future, water allocation between surface
392 water and groundwater) which may be useful as a basis for **expert-driven model evaluation**. While there

393 has been a significant amount of research and publications on MIPs including surface water availability,
394 limited multi-model assessments for large-scale groundwater studies exist. Important aspects of MIPs in
395 general could facilitate all three model evaluation strategies: community-building and cooperation with
396 various scientific communities and research groups, and making the model output publicly available in a
397 standardized format. **We therefore suggest that current MIPs could be modified and expanded to**
398 **explicitly consider these three model evaluation strategies which would leverage the value and effort**
399 **of ongoing MIPs to more comprehensively evaluate large-scale groundwater models while offering**
400 **more opportunities for experimental hydrologists to be involved in model assessment studies across**
401 **scales.**

402

403 **TOWARDS IMPROVED GROUNDWATER REPRESENTATION IN LARGE-SCALE MODELS**

404 Land surface, large-scale hydrologic and Earth System models increasingly represent groundwater,
405 which we envision will lead to a better understanding of large-scale water systems and to more
406 sustainable water resource use. We call on various scientific communities to join us in this effort to
407 improve the representation of groundwater in continental to global models using the specific
408 recommendations we make for **transparent conceptualization, systematic classification, and holistic**
409 **evaluation**. As described by examples above, we have already started this journey using open science
410 (data, models, publishing and collaboration) and more holistic approaches (meaning holistic
411 representation of hydrologic processes as well as more holistic model evaluation). We hope this will lead
412 to better outcomes especially for the goals of including groundwater in large-scale models that we
413 started with above: improving our understanding of Earth system processes through more robust
414 conceptualization and evaluation; and informing water decisions and policy by enhancing the trust of

415 stakeholders through increased transparency. Together we can better understand what has always been
416 beneath our feet, but often forgotten or neglected.

417

418 **Acknowledgements:**

419 This community project was directly supported by a Benjamin Meaker Visiting Professorship at the
420 Bristol University to TG and a Royal Society Wolfson Award to TW (WM170042). We thank many
421 members of the community who contributed to the discussions, especially at the IGEM workshop in
422 Taiwan.

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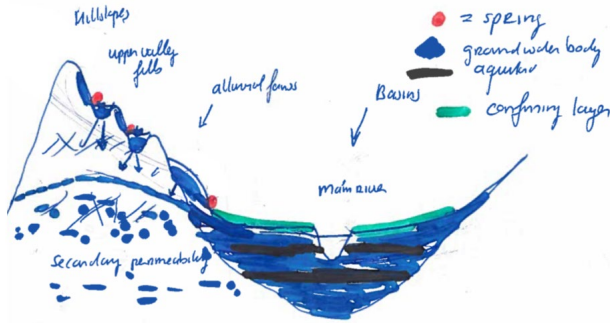
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738 **Table 1. Current and future observational data that could be used to evaluate large-scale models, categorized by**
 739 **current availability and generally arranged from globally distributed to local scale within each category. Data**
 740 **included here are directly linked to groundwater variables (recharge, storage, or discharge). In the future, other**
 741 **data such as evapotranspiration and or soil moisture could also be considered as useful constraints on**
 742 **groundwater fluxes and stores.**

| Data type | Strengths | Limitations | Spatial Attributes | Availability |
|--|---|--|--|---|
| Existing Data Sources | | | | |
| GRACE total water storage anomalies | Globally available | Groundwater changes are model remainder; coarse resolution and limited period | Gridded and spatially continuous | Rodell et al. (2018) |
| Perennial stream map | Globally available and could be compared to streamflow observations | Not all perennial streams reaches are groundwater-influenced; does not provide information about magnitude of inflows/outflows. | Spatially continuous along stream networks | Schneider et al. (2017) Cuthbert et al. (2019) |
| Baseflow | Constrains direction and magnitude of fluxes at groundwater system boundaries. | Derived from streamflow observations; limited to basins with observations. Relevant processes occur at sub-grid-cell resolution. | Point observations at measurement locations | Beck et al. (2013). |
| Water table depth or fluctuations | Can provide information on performance away from model boundary conditions. | Water table fluctuations available at few locations and water table depth observations biased towards North America and Europe | Point measurements at existing wells | Water table depth from Fan et al. (2013) |
| Potential Future Data Sources | | | | |
| Gaining or losing stream reaches | Multiple techniques for measurement (interpolated head measurements, streamflow data, water chemistry). Constrains direction of fluxes at groundwater system boundaries | Relevant processes occur at sub-grid-cell resolution. | Spatially continuous along stream networks | Not globally available but see Bresciani et al. (2018) for a regional example |
| Springs and groundwater-dependent surface water bodies | Constrains direction of fluxes at groundwater system boundaries | Relevant processes occur at sub-grid-cell resolution. | Point measurements at water feature locations | Springs available for various regions (e.g. Springer, & Stevens, 2009) but not globally |
| Tracers (heat, isotopes or other geochemical) | Provides information about temporal aspects of groundwater systems (e.g. residence time) | No large-scale models simulate transport processes (Table S1) | Point measurements at existing wells or surface water features | Isotopic data compiled (Gleeson et al., 2016; Jasechko et al., 2017) but no global data for heat or other chemistry |

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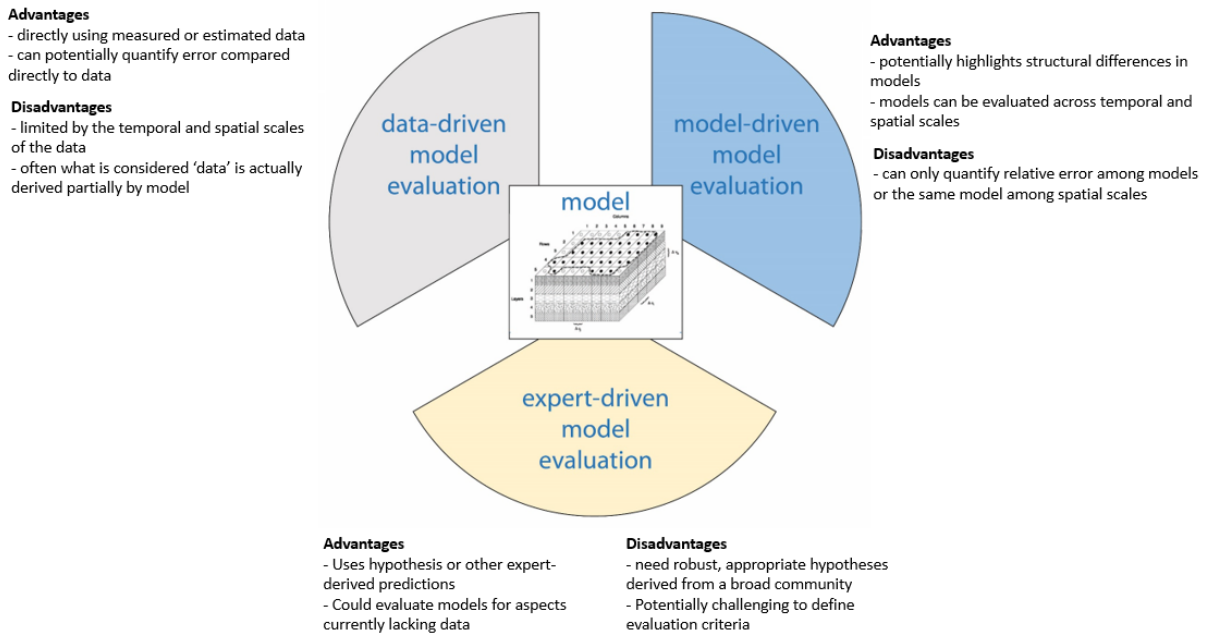
745 **Figure 1: The conceptual model underlying some of the development of PCR-GLOBWB coupled with MODFLOW**

746 **(De Graaf et al. 2017), which has never been previously published. Ideally conceptual models should also**

747 **explicitly include recharge, flow and discharge patterns.**

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751 **Figure 2: A framework for evaluating groundwater in large-scale models, with the large-scale model**

752 **being in the centre of the framework surrounded by the three strategies. Strategies include data-,**

753 **model-, and expert-driven model evaluation, each which have advantages and disadvantages.**

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755 **Supplementary Information**

756

757 **Table S1. Model classification based on three models classes and various model characteristics; see link to**

758 **[google doc](#) to view easier or edit (google doc will be migrated to a community github page)**

| Table 1. Model classification for large-scale models representing groundwater (1) | lateral groundwater flow to a river within a cell | | | | | | | 2D lateral groundwater flow between all cells | | | | 3D groundwater flow | |
|---|---|---|---|--|--|--|--|---|---|--|--|--|--|
| | No GW flow | one-way | | | two-way | | | one-way | | two-way | | | |
| | | yes | | | | | | no | | | | | |
| groundwater flow | JULES | ORCHIDEE | LM3 | VIC-ground | CLM5 | TOPLATS | Catchment | WaterGAP2-G3 M | LEAF hydro | PCRGLOB-WB - MODFLOW | ISBA-TRIP | HydroGeoSphere | ParFlow |
| groundwater-surface coupling (2) | | Recharge = P-R-ET | Recharge = P-R-ET | Recharge depends on WT head and capillary fluxes | Recharge depends on WT head and capillary fluxes | Recharge depends on WT head and capillary fluxes | Recharge depends on WT head and capillary fluxes | currently uncoupled | recharge derived from WGM | Recharge depends on WT head and capillary fluxes | Recharge depends on WT head and capillary fluxes | directly represented | directly represented |
| surface-atmosphere coupling | | | | | | | | | | | | | |
| example model (3) | | | | | | | | | | | | | |
| groundwater recharge (diffuse) | Free-drainage | Recharge = P-R-ET | Recharge = P-R-ET | Recharge depends on WT head and capillary fluxes | Recharge depends on WT head and capillary fluxes | Recharge depends on WT head and capillary fluxes | Recharge depends on WT head and capillary fluxes | currently uncoupled | recharge derived from WGM | Recharge depends on WT head and capillary fluxes | Recharge depends on WT head and capillary fluxes | directly represented | directly represented |
| focused recharge (4) | not represented | optional (via enhanced infiltration in ponds) | not represented | not represented | not represented | not represented | not represented | represented after coupling | not represented | represented from lakes and perennial rivers? | not represented | not represented | not represented |
| surface water boundary condition or coupling | not represented | not represented | not represented | not represented | not represented | not represented | not represented | currently uncoupled with boundary condition using conductance | no head-based interactions with surface water | one-way coupling with three boundary conditions including drainage from linear reservoir | directly represented | directly represented | directly represented |
| variably saturated or partially saturated (5) | 1D Richards' in soil layers | 1D Richards' in soil layers | 1D Richards' in soil layers | 1D Richards' in soil layers | 1D Richards' in soil layers | 1D Richards' in soil layers | Lumped 3D Richards | partially saturated | partially saturated | vertical fluxes in soils depending on soil saturation and GW level | 1D Richards' in soil layers | variably saturated using 3D Richard's equation | variably saturated using 3D Richard's equation |
| water table and hydraulic head | Optional WT diagnostic based on TOPMODEL | not represented | represented, parameterised | directly represented | First layer from bedrock where soil moisture < 0.9 | represented following TOPMODEL | represented following TOPMODEL | directly represented | directly represented | directly represented | directly represented | directly represented | directly represented |
| groundwater storage | not represented | represented as linear reservoir | represented | represented | represented | represented | represented | directly represented | represented | directly represented | directly represented | directly represented | directly represented |
| lateral flow | not represented | represented | represented through lateral flow divergence | parameterized following Francini and Pacciani (2001) | parameterized, calibration parameter related to baseflow | represented following TOPMODEL | represented following TOPMODEL | directly represented but not long flowlines | directly represented | directly represented | directly represented | directly represented | directly represented |
| groundwater bottom boundary condition | gravity drainage from soil | function of reservoir | no flux | no flux | no flux | no flux | no flux | no flux | no flux | no flux | no flux | no flux | no flux |
| groundwater use | not represented | not represented | not represented | not represented | not represented | not represented | not represented | to be included in future | not represented | represented | not represented | not represented | not represented |
| preferential flow | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented |
| groundwater temperature | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented |
| groundwater quality | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented |
| groundwater density | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented |
| confined conditions | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | represented | not represented | not represented | not represented |
| coupling with ocean (and ocean models) | no | no | no | no | no | no | no | no | ocean boundary condition | ocean boundary condition | ??? | ocean boundary condition | possible |
| isotope-enabled | no | no | no | no | no | no | no | no | no | no | no | no | no |
| Included in current assimilation schemes | yes | ??? | no | no | yes | ??? | no | no | no | no | no | no | no |
| paleo groundwater | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented | not represented |
| Reference | Best et al. (2011) | Guilberteau et al. (2011) | Milly et al. (2014) | Liang et al. (2003) | Andre et al. (2018) | Famiglietti & Wood (2006) | Koster et al. (2000) | Reinecke et al. (2011) | Fan et al. (2013) | de Graaf et al. (2017) | Vergnes et al. (2014) | Brunner and Simmer (2013) | Maxwell et al. (2017) |

Notes:
 (1) Only the most RECENT version of models with published results at continental to global scales are included. Analytical solutions (including the water table ratio or groundwater response times) are not described here.
 (2) One-way coupling means that S <-> M <-> recharge <-> GW <-> stream flow, but no reverse influence; in this case, the GW model is dependent on surface simulations to provide recharge. Two-way coupling means there is a fully coupling of surface and groundwater.
 (3) Other models exist with similar features.
 (4) Focused recharge refers to any recharge that occurs beneath water bodies such as streams or lakes; whereas preferential flow means recharge that bypasses the soil matrix during diffuse recharge through fractures or other macropores.
 (5) Variably saturated means that the saturation, and related constitutive relations can vary continuously, while partially saturated means that saturation can only discretely vary between fully saturated and unsaturated.

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