

1 **A spatially hybrid hydrological modeling approach based on**
2 **spatial heterogeneity of watershed characteristics**

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Abstract:

The model structure of a hydrological model is primarily ~~determined~~ defined by its spatial discretization scheme and the representation of hydrological processes. ~~A~~ Spatially consistent model structures ~~are~~ is often inadequate for addressing diverse application contexts, particularly in complex watersheds with significant spatial heterogeneity. Hydrological modeling frameworks enable comprehensive watershed modeling by constructing and integrating various model structures, each tailored to a specific area. While the state-of-the-art frameworks typically support model structures composed of lumped spatial units and conceptual simulation algorithms, they often lack support for spatially distributed units and physically-based algorithms. This paper proposes a spatially hybrid hydrological modeling approach that enables the flexible combination of compatible spatial units and simulation algorithms to construct different model structures for individual subbasins within a watershed, such as lumped conceptual and fully-distributed semi-physically-based model structures. These subbasin-~~level~~ model ~~structures~~ are coherently ~~then~~ integrated through channel routing to perform ~~for~~ watershed-scale simulation. The proposed approach was implemented using the Spatially Explicit Integrated Modeling System (SEIMS) and evaluated by a case study in a medium-sized watershed. Two distinct model structures were designed: a lumped conceptual model structure for gently sloping subbasins and a fully-distributed semi-physically-based model structure for mountainous subbasins. Experimental results ~~showed~~ demonstrate that the hybrid model ~~combines~~ the strengths of both individual model structures, achieving ~~improved~~ ing general performance while ~~also~~ inheriting some limitations, such as simulation bias from the conceptual model. More importantly, the case study highlights the enhanced flexibility in hydrological modeling of the proposed approach and its potential to support more rational and adaptive hydrological modeling in spatially heterogeneous watersheds.

Keywords: Watershed simulation; hydrological modeling framework; spatially hybrid model structure; spatial heterogeneity; SEIMS

Highlights

- An approach for spatially hybrid hydrological model structures is proposed.
- Model structure flexibly combines compatible spatial units and simulation algorithms.
- Subbasin-level model structures are integrated for watershed-scale simulation.
- Subbasin, hillslope, HRU, and cells support conceptual or semi-physical algorithms.
- Spatially hybrid model improved general performance but also inherited limitations.

20 **1 Introduction**

21 Hydrological models serve as effective tools for simulating and enhancing our
22 understanding of complex hydrological processes in real-world watersheds. A variety
23 of hydrological models have been developed, each suited to different application
24 contexts depending on watershed characteristics, available data, and other related
25 factors (Beven, 2000; Gharari et al., 2021; Wagener et al., 2001). Hydrological
26 models can be classified from two perspectives that define their model structures: the
27 spatial discretization scheme (such as lumped and semi- or fully-distributed models)
28 and the representation of hydrological processes (such as conceptual and semi- or
29 fully-physically-based models) (Chow, 1988; Milad et al., 2012; Dingman, 2015;
30 Hrachowitz and Clark, 2017). The determination of an application-specific model
31 structure, involving the decision of ~~the~~ appropriate spatial discretization scheme and
32 hydrological process representations, stands as the primary and critical step in
33 hydrological modeling (Butts et al., 2004; David et al., 2022; Pilz et al., 2020; van
34 Esse et al., 2013).

35 The spatial discretization scheme refers to the arrangement of one or more types
36 of spatial units within the watershed for hydrological modeling, which are derived
37 from spatial data including terrain, land use, soil, and others (Dehotin and Braud,
38 2008). Spatial units for lumped hydrological models typically ignore or broadly
39 generalize the spatial heterogeneity of watershed characteristics using dominant
40 geographic attribute domain, such as the dominant hydrological response unit

41 (DominantHRU). The DominantHRU often refers to HRUs defined by dominant soil
42 types, land use types, and slope classes within each subbasin (Arnold et al., 2010). In
43 this regard, a subbasin or even an entire watershed ~~or subbasins~~ could also be defined
44 as one DominantHRU ~~for lumped hydrological models~~. In contrast, spatial units for
45 semi- or fully-distributed hydrological models can fully cover the entire geographic
46 spatial domain of the watershed at varying levels of details. These include HRUs
47 defined by unique combinations of selected geographic attributes within each
48 subbasin (FullHRU, where one HRU may consist of several spatially separated areas;
49 Dile et al., 2016), spatially explicit HRUs (ExplicitHRU, where each HRU is a
50 spatially independent and contiguous area; Teshager et al., 2016), and grid cells
51 (Wigmosta et al., 1994). It should be noted that the term HRU is a broad concept that
52 can be specifically defined as lumped units (DominantHRUs), semi-distributed units
53 (FullHRUs), and fully-distributed units (ExplicitHRUs). From this perspective, the
54 widely used SWAT (Soil and Water Assessment Tool; Arnold et al., 1998) model can
55 be applied as either a lumped or semi-distributed hydrological model, depending on
56 the HRU definitions used. However, it cannot be considered a fully-distributed model,
57 as it does not consider lateral flow processes between HRUs.

58 The representation of hydrological processes denotes the simulation algorithms
59 of real-world hydrological phenomena (e.g., evaporation, infiltration, and surface and
60 subsurface flow routing) through mathematical equations, numerical solutions, and
61 spatiotemporal discretization. Conceptual representations simplify hydrological

62 processes within a watershed into a few lumped components, typically including
63 water storage, water losses, and flow routing. They are often implemented using
64 conceptual reservoirs (or buckets), such as linear method or two-reservoir method for
65 runoff prediction. Parameters in conceptual models often lack explicit physical
66 interpretation and are typically estimated via calibration (Fenicia et al., 2011; Knoben
67 et al., 2019). In contrast, fully-physically-based representations apply fundamental
68 physical laws to simulate the conservation of mass, momentum, and energy in both
69 vertical and lateral directions (Abbott et al., 1986). This is commonly achieved by
70 solving coupled partial differential equations, such as the Richards' equation for
71 unsaturated flow and Saint-Venant equations for surface flow, as implemented in
72 models like MIKE SHE (Système Hydrologique Européen; [Abbott et al., 1986](#)~~Graham~~
73 ~~and Butts, 2005~~) and SHUD (Simulator for Hydrologic Unstructured Domains; [Shu et](#)
74 [al., 2020](#)). While offering high-fidelity representations of hydrological processes, they
75 often involve extensive data requirements and high computational complexity. To
76 address the trade-off between physical realism and computational feasibility, semi-
77 physically-based representations employ simplified physical equations for individual
78 hydrological processes while avoiding full numerical coupling. These processes are
79 generally simulated independently. Although empirical components may be included,
80 most model parameters retain clear physical interpretations and often can be estimated
81 from field observations. ~~PA~~ prominent examples utilizing semi-physically-based
82 representations ~~include~~ SWAT (Arnold et al., 1998) ~~and~~ [RHESys \(Regional Hydro-](#)

83 Ecologic Simulation System; Tague and Band, 2004).

84 It is important to note that the classification of hydrological process
85 representations is not absolute. Even fully-physically-based models, as defined above,
86 may lose some of their physical grounding when applied at coarse spatial scales. This
87 is due to the generalization of watershed spatial heterogeneity through “representative
88 parameters”, which renders physically-based models into an effective conceptual
89 application of the underlying equations. This issue arises largely from the absence of
90 well-established upscaling laws in hydrology (Dooge, 1986; Beven, 1989, 2000;
91 Sivapalan et al., 2003), i.e., theoretical methods for transferring physical equations
92 derived at a fine scale to a coarser scale. Nevertheless, for the purpose of~~in~~ this study,
93 we follow the aforementioned classification and primarily focus on the conceptual
94 and semi-physically-based representations.

95 Existing methods of determining model structures can be categorized as
96 spatially consistent method and spatially varying method. The spatially consistent
97 model structure means the types of spatial units (also referred to as simulation units)
98 and simulation algorithms for hydrological processes are the same for the whole
99 watershed. Most research on directly choosing a single existing hydrological model
100 with a fixed or near-fixed model structure falls into this category. Such model
101 structures are often developed with specific assumptions and suitable for constrained
102 application contexts. ~~They vary from lumped to fully distributed spatial discretization~~
103 ~~schemes, and from conceptual to fully physically based representation of~~

104 ~~hydrological processes.~~Based on the most typical configuration or usage of ~~each~~
105 ~~existing~~ models, examples include: the lumped and conceptual HBV (Hydrologiska
106 Byråns Vattenbalansavdelning; Lindström et al., 1997) and GR4J (modèle du Génie
107 Rural à 4 paramètres Journalier; Perrin et al., 2003); the semi-distributed and semi-
108 physically-based TOPMODEL (TOPography based hydrological MODEL; Beven and
109 Kirkby, 1979), SWAT, and RHESSys (~~Regional Hydro-Ecologic Simulation System;~~
110 ~~Tague and Band, 2004~~); the fully-distributed and semi-physically-based DHSVM
111 (Distributed Hydrology Soil Vegetation Model; Wigmosta et al., 1994) and the
112 rasterized RHESSys named CHESS (Coupled Hydro-Ecological Simulation System;
113 Tang et al., 2019); and the fully-distributed and fully-physically-based MIKE SHE,
114 SHUD, and ParFlow (Kollet and Maxwell, 2006). Adopting a spatially consistent
115 model structure inherently assumes that the spatial variability of watershed
116 characteristics can be adequately captured by the required input data and parameters
117 ~~required by the chosen model structure~~. Nevertheless, a fixed ~~or near-fixed~~ model
118 structure often lacks flexibility in adapting simulation units and incorporating
119 alternative simulation algorithms for considered hydrological processes. For example,
120 models that rely solely on the infiltration-excess runoff mechanism are unsuitable for
121 watersheds where saturation-excess runoff dominates. Therefore, using a rigid-fixed
122 model structure may fail to effectively accommodate diverse and complex application
123 contexts (Ley et al., 2016; Savenije, 2009).

124 To address the limitations of using fixed model structures ~~and accommodate~~

125 ~~complex application contexts with greater flexibility in determining the model~~
126 ~~structure~~, researchers have increasingly turned to modular hydrological modeling
127 frameworks, such as SUMMA (Structure for Unifying Multiple Modeling
128 Alternatives; Clark et al., 2015), ECHSE (ECo-Hydrological Simulation
129 Environment; Kneis, 2015), MARRMoT (Modular Assessment of Rainfall–Runoff
130 Models Toolbox; Knoben et al., 2019), SEIMS (Spatially Explicit Integrated
131 Modeling System; Liu et al., 2016; Zhu et al., 2019), and Raven (Craig, 2020). These
132 frameworks emphasize various aspects of flexibility in customizing application-
133 specific model structures, including extensible types of simulation units and
134 associated simulation algorithms (Kneis, 2015), alternative simulation algorithms for
135 individual hydrological processes (Zhu et al., 2019), and alternative simulation
136 algorithms for each conceptual hydrological component ~~of hydrological processes~~
137 (Craig, 2020). By supporting the concept of “multiple working hypotheses” ~~(Clark et~~
138 ~~al., 2011)~~, these frameworks facilitate studies on the suitability ~~and uncertainty~~ of
139 alternative model structures across spatial and temporal scales, thus enabling analysis
140 of their scale-dependent applicability and the propagation of uncertainty ~~–(Clark et~~
141 ~~al., 2011; David et al., 2022; Kiraz et al., 2013; Knoben et al., 2020; Shu et al., 2020).~~
142 However, the primary focus of these frameworks remains on customizing and
143 applying a spatially consistent model structure across the entire watershed. This
144 spatial consistency may be unreasonable and inaccurate to capture the dominant
145 hydrological processes in application contexts exhibiting significant spatial

146 heterogeneity (~~Gao et al., 2018~~; Sui and Turner, 2021).

147 Recognizing the limitation of spatially consistent model structures, researchers
148 have explored constructing spatially varying model structures within watersheds in
149 two principal approaches. The first involves externally integrating multiple individual
150 models, either manually (Liu et al., 2020; Li et al., 2021; Wang et al., 2021b) or
151 through unified model interoperable interfaces such as ESMF (Earth System
152 Modeling Framework; Hill et al., 2004) and OpenMI (Open Modeling Interface;
153 Harpham et al., 2019). However, the flexibility of such model-level integration may
154 be limited by the inherent fixed ~~or near-fixed~~ model structures of each integrated
155 model. Furthermore, different interoperable interfaces often need to be separately
156 implemented for each model, posing considerable challenges for hydrologists lacking
157 programming expertise.

158 To further enhance the flexibility of spatially varying model structures, another
159 idea involves internally constructing and integrating multiple model structures within
160 a single modular hydrological modeling framework such as FLEX-Topo
161 (Topography-driven Flux Exchange hydrological model; Gao et al., 2014; Savenije,
162 2010), SUPERFLEX (SUPER Flux Exchange hydrological model; Fenicia et al.,
163 2011, 2016), and airGR (Suite of GR Hydrological Models; Coron et al., 2017;
164 Thébault et al., 2023). These frameworks allow the assignment of different model
165 structures to different modeling areas within the watershed with only minimal
166 changes to configuration or source code. Nevertheless, these frameworks are

167 fundamentally limited to conceptual representations of hydrological processes, with
168 simulation units typically being subbasins, DominantHRUs, or FullHRUs. Therefore,
169 these state-of-the-art flexible frameworks primarily support lumped or semi-
170 distributed conceptual model structures and thus face a significant challenge in
171 integrating physically-based simulation algorithms and spatially explicit distributed
172 simulation units, such as grid cells, where spatial relationships between units are
173 maintained to support routing related~~enable the execution of physically-based~~
174 simulation algorithms. This limitation also constrains the exploration of suitable
175 perceptual models for specific applications (Beven, 2012; Wang et al., 2021a).

176 To address the inability of existing hydrological modeling frameworks to support
177 spatially varying distributed physically-based model structures, we propose a new
178 and practically significant spatially hybrid modeling approach. In this approach,
179 compatible types of simulation units and simulation algorithms can be combined to
180 construct different model structures for each subbasin within the watershed, such as
181 lumped conceptual, lumped semi-physically-based, semi-distributed semi-physically-
182 based, and fully-distributed semi-physically-based model structures. Subbasin-level
183 model structures ~~are~~can then be coherently integrated through channel routing to
184 perform ~~the~~ watershed-scale simulation. The remainder of this paper is organized as
185 follows: Section 2 outlines the design of the proposed approach and its
186 implementation based on the SEIMS framework, Section 3 presents an experimental
187 case study, followed by discussion in Section 4, and the conclusion in Section 5.

2 Method design and implementation

2.1 Basic idea

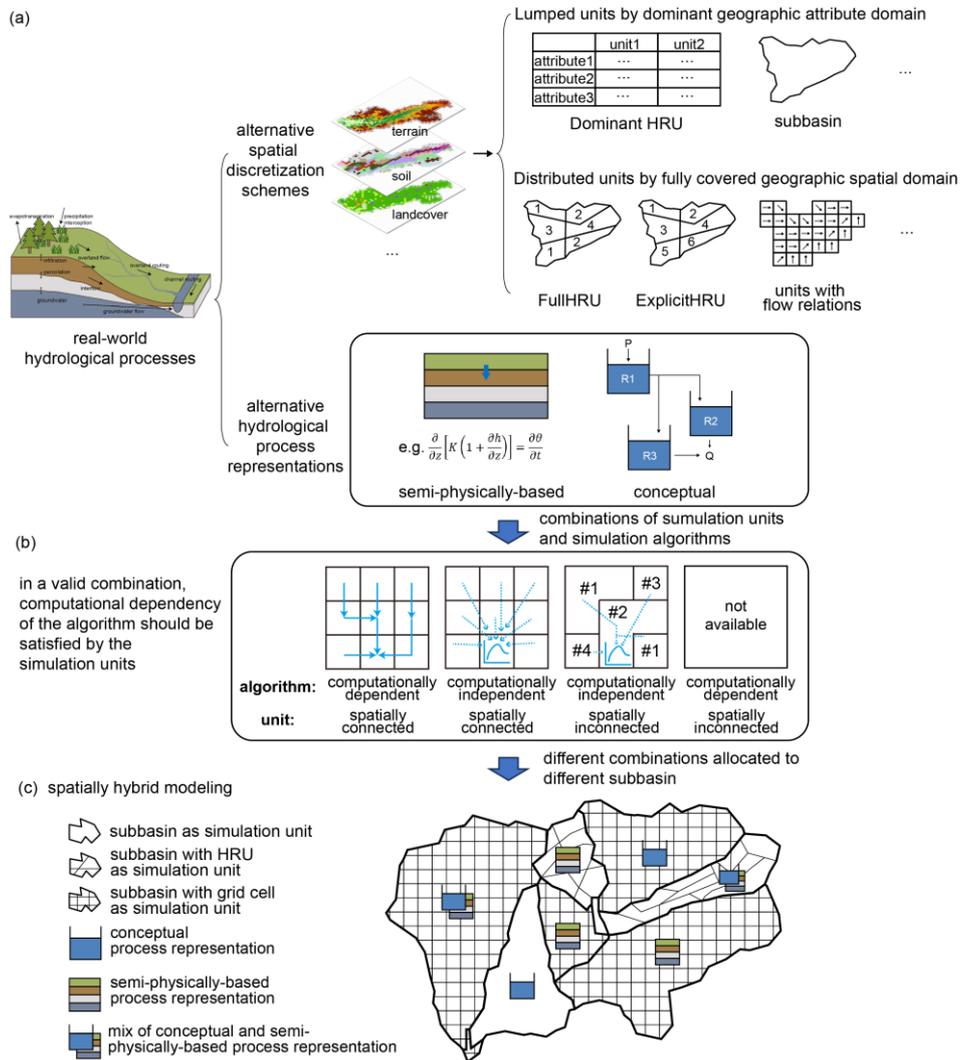
The basic idea of the proposed spatially hybrid hydrological modeling approach is to construct and execute different model structures for relatively independent areas within the watershed in a divide-and-conquer manner. Given that subbasins are relatively closed catchment areas connected by the watershed drainage channel network, they serve as ideal modeling units, each configurable with an individual model structure. Therefore, the core design of the proposed approach involves two key aspects: 1) flexibility in model structure construction, which enables the combination of different simulation units and simulation algorithms, and 2) the capability to distribute these individual model structures to subbasins of the watershed and integrate their execution within a unified time loop.

The core concept for designing flexibly constructed model structure involves decoupling hydrological process representations (i.e., simulation algorithms) from specific spatial discretization scheme (i.e., simulation units). For instance, the physically-based algorithms are typically applied to fine-scale units such as grid cells, for both are assumed to describe the hydrological process in detail. Similarly, conceptual algorithms are typically associated with lumped or coarse-scale units such as DominantHRUs, hillslopes, or subbasins. However, this rigid binding is not always necessary. Conversely, combining different model structure components has proven effective, as evidenced by various studies (Gunduz and Aral, 2005; Liu et al., 2020;

209 Sidle, 2021). Simulation algorithms can be classified as computationally dependent
210 and computationally independent based on their inter-unit computational dependency.
211 The simulation of a computationally dependent algorithm on one simulation unit often
212 relies on the water flows or state variables of its adjacent or upstream units, whereas a
213 computationally independent algorithm simulates independently for each unit (Figure
214 1b). Similarly, simulation units can be categorized as spatially connected and spatially
215 disconnected depending on whether spatially explicit relationships exist between units
216 (Figure 1a).

217 Therefore, three compatible combinations of simulation algorithms and
218 simulation units can be identified: 1) computationally dependent algorithm with
219 spatially connected units, 2) computationally independent algorithm with spatially
220 connected units, and 3) computationally independent algorithm with spatially
221 disconnected units (Figure 1b). For instance, a conceptual reservoir-based surface
222 runoff generation algorithm integrated with a physically-based kinematic wave-based
223 surface routing can be applied to grid cells, where computational dependency is
224 satisfied by the flow directions between grid cells. Another example is the integration
225 of a physically-based Green-Ampt surface runoff generation algorithm with a
226 conceptual unit hydrograph-based surface routing algorithm for application on HRUs
227 (Craig, 2020), requiring no computational dependency. It is crucial to note that while
228 computational dependency is a fundamental constraint, the ultimate rationality of a
229 chosen model structure relies on the modeler's hydrological knowledge and specific

230 application requirements.



231

232 Figure 1. Design of the proposed spatially hybrid hydrological modeling approach. a)

233 decoupling the simulation of hydrological processes into spatial discretization

234 schemes and hydrological process representations; b) supporting compatible

235 combinations of simulation algorithms and simulation units; and c) enabling the

236 spatial varying allocation of different model structures at the subbasin level.

237

238 Based on the above idea ~~of flexible model structure construction approach~~, this

239 study considers the spatial heterogeneity of watershed characteristics by treating each

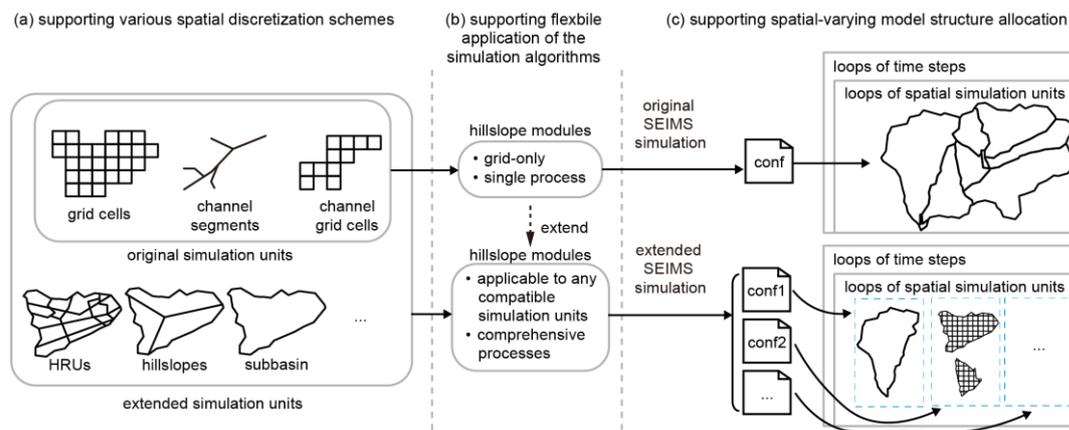
240 subbasin unit as the modeling unit. Each subbasin is configured with an individual

241 subbasin model structure to simulate hillslope processes and the channel routing
242 process., which are then integrated into a comprehensive watershed model via channel
243 routing processes (Figure 1c). A subbasin model structure can either encompass all-
244 hydrologic process holistically or, more commonly, separately consider hillslope-
245 processes and the channel routing process. Therefore, Different subbasin model
246 structures can be constructed, such as conceptual algorithms with subbasin as
247 simulation unit, semi-physically-based algorithms with grid cells as simulation units,
248 and a mix of conceptual and semi-physically-based algorithms with HRU as
249 simulation units for hillslope process and a conceptual algorithm for the channel
250 routing process (Figure 1c). Since it is assumed in this study that mass and energy
251 only exchange between subbasins through channel routingnetwork, the channel
252 routing components within each subbasin model structure (e.g., the Muskingum
253 method) are used to couple with their upstream and downstream subbasins, thereby
254 integrating all subbasin model structures into a collectively form the comprehensive
255 overall watershed model structure (Figure 1c)by interconnecting through the-
256 drainage network with upstream-downstream relationships. The execution of a
257 downstream subbasin relies on the output of its upstream subbasins. This dependency
258 implies that subbasin executions without upstream-downstream relationships can be
259 parallelized to improve computing efficiency, while those with dependencies must be
260 executed sequentially.

261

262 **2.2 Design of the spatially hybrid hydrological modeling**
 263 **approach using SEIMS hydrological modeling framework–**
 264 **SEIMS**

265 Following the above basic idea, the proposed spatially hybrid hydrological
 266 modeling approach was designed using the SEIMS framework for its flexible modular
 267 design and two-level parallelization strategy (Liu et al., 2016; Zhu et al., 2019). To
 268 support the flexible construction of model structures–construction of the proposed–
 269 approach, the spatial discretization schemes of SEIMS should be expanded (Figure
 270 2a; Section 2.2.2), the simulation modules of hillslope processes should be upgraded
 271 to accommodate compatible simulation units (Figure 2b; Section 2.2.2), and the
 272 execution of SEIMS-based model should be upgraded to allocate different model
 273 structures to subbasins and executed in an integrated way (Figure 2c; Section 2.2.3).



274 Figure 2. Overall design of extending the SEIMS (Spatially Explicit Integrated
 275 Modeling System) to implement the proposed spatially hybrid hydrological modeling
 276 approach: a) supporting various spatial discretization schemes; b) supporting applying
 277 simulation algorithms of hillslope processes to compatible simulation units; and c)
 278 supporting spatial varying model structure allocation on the subbasin level to
 279 construct a watershed model.
 280

281 **2.2.1 Brief introduction to SEIMS**

282 As a hydrological modeling framework, SEIMS provides users with the
283 complete toolchain to preprocess modeling data, construct and execute the SEIMS-
284 based model, analyze the parameter sensitivity, and so on (Liu et al., 2021; Zhu et al.,
285 2019). More importantly, SEIMS supports developers in adding simulation modules
286 of hydrologic processes following three developing principles. ~~The principles are~~
287 ~~briefly introduced in three aspects~~: the spatial discretization scheme, the modular
288 modeling design, and the parallelization strategy.

289 **(1) Spatial discretization scheme**

290 SEIMS primarily adopts a two-level spatial discretization scheme, i.e., the
291 “subbasin-basic simulation unit.” In the stage of preprocessing modeling data, SEIMS
292 delineates the watershed into subbasins, each with one channel. Within each subbasin,
293 the basic simulation units (i.e., grid cells in the original version) are delineated and
294 organized as a one-dimension array with their actual positions recorded. Most
295 simulation modules of hillslope processes use grid cells as simulation units, while a
296 few modules use subbasin units such the linear reservoir algorithm for the
297 groundwater process. Modules of channel routing processes use channel lines or grid
298 cells as simulation units. All parameters required by the modules on these simulation
299 units are prepared using the data preprocessing ~~tools~~scripts of SEIMS. The grid cells
300 are layered within each subbasin based on the flow direction of each cell (i.e., the
301 single flow direction in the original version; Liu et al., 2014). The layers are used in

302 modules of hillslope surface or subsurface flow routing processes to determine the
303 simulation sequences of grid cells. The same idea is used for layering subbasins and
304 channels.

305 **(2) Modular modeling design**

306 A SEIMS-based hydrological model is constructed by the SEIMS main program
307 and several user-configured modules of hydrologic processes in a text-based format
308 rather than hard-coded. The main program controls the time loop of the simulation
309 and repeatedly invokes the selected modules in sequence. Each module is responsible
310 for the simulation of one or several hydrologic processes on corresponding simulation
311 units in different orders. For instance, the potential evapotranspiration module
312 executes on every grid cell in an arbitrary order, the subsurface flow (also referred to
313 as interflow) routing module executes on every grid cell by layering orders (Liu et al.,
314 2014), and the channel routing module executes on each channel by upstream-
315 downstream orders.

316 In SEIMS, each module should handle its required simulation conditions. Users
317 should decide the integration feasibility of the module combinations to meet the
318 requirements of each module, including the boundary conditions when calculating
319 vertical and lateral water movements. For instance, to implement a semi-physically-
320 based interflow module based on the Darcy's Law, the boundary condition could be
321 set either with the hydraulic gradient equal to the slope at each cell, or dynamically
322 determined by the outputs of modules from adjacent subbasins.

323 Each module inherits from a standard module interface, including the definitions
324 of input data, parameters, and output data. The input data and parameters of one
325 module can be either read from the database created during the preprocessing stage or
326 referred from other modules during the runtime. Each module itself initializes its
327 output data. In this way, during the execution of the SEIMS-based model, the same
328 variable is shared among modules.

329 **(3) Two-level parallelization strategy**

330 Since SEIMS treated subbasins as relatively independent modeling units for
331 hydrological modeling, the first level of the two-level parallelization strategy
332 dispatches the simulation of subbasins to different computing processes (or nodes)
333 through the Message Passing Interface (MPI) (Liu et al., 2016). The second level is
334 achieved within each subbasin by dispatching the simulations of grid cells without
335 mutual dependencies to computing threads via Open Multi-Processing (OpenMP)
336 (Liu et al., 2014). Based on the design of the modular structure, variables required to
337 be communicated among subbasins only need to be defined in the metadata of each
338 module and will be handled by the SEIMS main program (Zhu et al., 2019). That
339 means the complicated MPI programming details are hidden from module developers.
340 Besides, the implementation of OpenMP-based parallelization only needs one line of
341 preprocessor directive code before the loop of computationally independent code.
342 Therefore, module developers can develop modules and build high-performance
343 hydrological models in a nearly serial programming way (Zhu et al., 2019). The two-

344 level parallelization strategy provides the potential to implement the proposed
345 approach in this study that applies different model structures to distinct subbasins.

346 **2.2.2 Constructing model structures with diverse simulation units and algorithms**

347 To enable the flexible construction of model structures based on SEIMS, the
348 diversity of both simulation units and simulation algorithms should be guaranteed. For
349 simulation units, the idea of constructing hydrological response units (HRUs) could
350 be added as simulation units of hillslope processes in SEIMS, including
351 DominantHRU, FullHRU, and ExplicitHRU (see the Introduction section for details;
352 Figure 1a) (Figure 2a). In terms of parameters, the physically-based parameters can be
353 derived from actual properties of the soil, landuse/landcover, and other spatial data,
354 while conceptual parameters are directly specified by lookup tables of soil and land-
355 use. For instance, the reservoir capacity of an HRU can be represented by the soil
356 depth associated with that specific HRU area, while some experimental coefficients
357 could be specified in the lookup tables. Under such an HRU discretization scheme,
358 the hillslope unit and subbasin unit can be regarded as specific DominantHRU to be
359 used as simulation units. Therefore, the extended SEIMS will offer the flexibility of
360 utilizing subbasins, hillslopes, HRUs, and grid cells as simulation units of hillslope
361 processes for various modeling needs.

362 For hydrological process representations, SEIMS was initially designed to
363 primarily integrate simulation algorithms of one hydrological process into each single
364 module, while it lacked a conceptual model capable of considering multiple

365 hydrological processes comprehensively (Figure 2b). To bridge this gap, lumped
366 conceptual models can be integrated as two separate hillslope modules: (1) a surface
367 runoff module that generate runoff at each basic simulation unit; and (2) a surface
368 routing module that convey runoff to the subbasin outlet. For instance, the
369 representative widely used conceptual model, GR4J (Perrin et al., 2003), is suitable to
370 be incorporated as a surface runoff module, coupled with a separate routing module
371 such as a simple accumulation method. Such module could be applied to any
372 simulation unit types stated above.

373 To ensure the combination compatibility of simulation algorithms with
374 simulation units applied to subbasins, the SEIMS module interface should be
375 extended to mark its computational dependency requirement as computationally
376 dependent or independent. A computationally dependent simulation module is
377 exclusively applicable to grid cells, and a computationally independent module is
378 applicable to any types of simulation unit. A model structure containing any
379 computationally dependent module can only be applied to the subbasin using grid
380 cells as the basic simulation units.

381 **2.2.3 Allocating individual model structures to subbasins and integrating as a** 382 **spatially hybrid watershed model structure**

383 An essential part of the spatially hybrid hydrological modeling approach is to
384 enable the separate allocation and execution of individual model structures to different
385 subbasins (referred to as ~~the~~ subbasin models) within the watershed. All subbasin

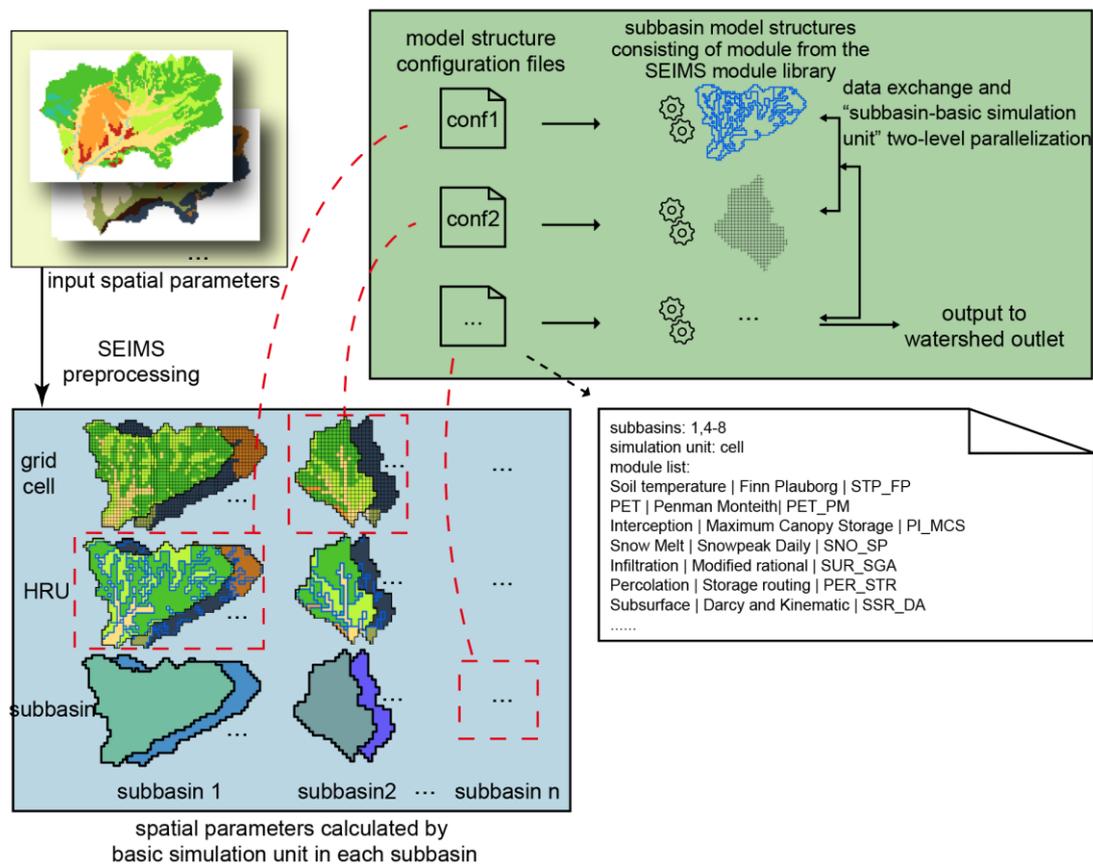
386 models are subsequently integrated as a watershed model. The requirements of
387 flexible model configuration and subbasin-separate simulation are compatible with
388 the text-based module configuration method and two-level parallelization strategy of
389 SEIMS, but still need improvement. The module configuration file of SEIMS should
390 be extended to designate a model structure to the specific subbasin, and the adopted
391 type of basic simulation units (Figure 3). In this way, the SEIMS main program
392 should be extended to can read the configuration file for each subbasin dynamically,
393 load simulation modules, and retrieve the modeling parameters according to the
394 specified basic simulation units.

395 The two-level parallelization strategy should be improved in two aspects. The
396 first is task scheduling of the subbasin-level parallelization for load balancing handled
397 by the SEIMS main program. The domain decomposition of subbasins should be
398 determined by upstream-downstream relationships between subbasins and the number
399 of basic simulation units of each subbasin in the runtime, rather than using the
400 numbers of grid cells of each subbasin in the preprocessing stage in the original
401 version of SEIMS (Liu et al., 2016). The second aspect concerns the parallelization at
402 the basic simulation unit level, which is handled in computationally independent
403 modules. This is inherently supported and easy to implement, as the OpenMP for-loop
404 can also apply to newly added basic simulation units such as HRUs.

405

406 **2.3 Implementation**

407 Based on the above method design, the implementation of the proposed approach
408 with SEIMS involves modifications to the data preprocessing tools, SEIMS main
409 programs, and SEIMS module library. The data preprocessing tools mainly include a
410 collection of Python scripts and C++ programs to delineate spatial units at different
411 scales (e.g., subbasins and hillslopes), extract spatial parameters of spatial units, and
412 create watershed modeling database (Zhu et al., 2019). In this study, a configurable
413 tool was implemented to support the delineation and parameterization of HRU-based
414 spatial units. This tool allows users to specify environmental variables (e.g., the
415 default land-use and soil types) to delineate HRU-based units. This tool also allows
416 specifying base spatial units and delineation strategy to generate different types of
417 HRU such as taking subbasins or hillslopes as base units to generate DominantHRU
418 or FullHRU. Therefore, the data preprocessing tools could prepare various types of
419 spatial unit and associated spatial parameters for each subbasin according to the user-
420 defined configuration file to meet various hydrological modeling scenarios. The
421 procedures of spatially hybrid modeling with SEIMS are depicted in Figure 3.



422

423 Figure 3. Procedures of spatially hybrid modeling with the SEIMS (Spatially Explicit
424 Integrated Modeling System)

425

426 The SEIMS main program, written in C++, was extended to read the

427 configuration file for each subbasin, load simulation modules and retrieve the

428 modeling parameters according to the specified simulation units. Simulation modules

429 of the SEIMS module library were updated to declare the type of computational

430 dependency. New conceptual simulation modules were added such as GR4J for

431 simulating hillslope runoff generation. With the above briefly introduced

432 implementation of the proposed approach, SEIMS can now support users in

433 constructing spatially hybrid model structures for considering spatial heterogeneity of

434 the watershed, where each subbasin may be simulated with different combinations of
435 conceptual or semi-physically-based simulation modules and spatial units.
436 Consequently, 42 modules are available after the implementation of this study
437 (detailed in Table S1 of the supplementary material), supporting simulation of
438 processes including snowfall, atmospheric deposition, snow balance, interception, soil
439 temperature, glacier, surface runoff, evapotranspiration, infiltration, percolation,
440 interflow, groundwater, channel routing, plant growth, and soil erosion.

441 The SEIMS is open-source on GitHub (<https://github.com/lreis2415/SEIMS>) and
442 is under continuous development.

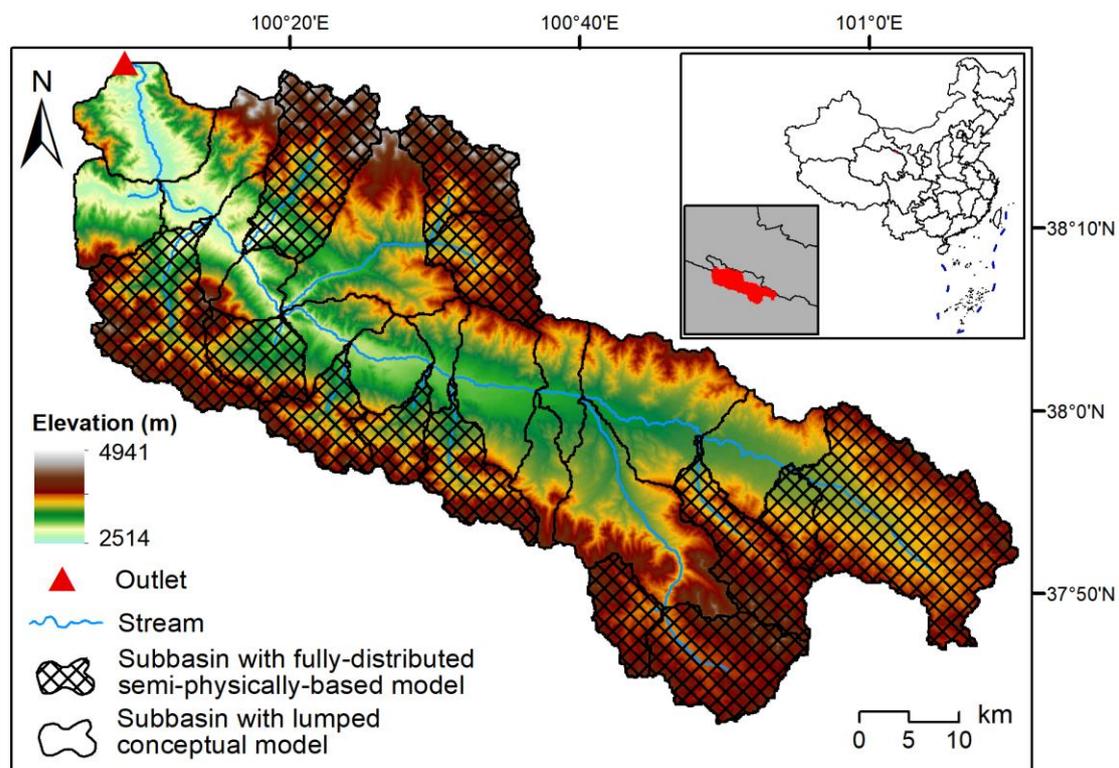
443 **3 Case study**

444 **3.1 Study area and data**

445 In this study, we selected the Babao River watershed at Qilian, Qinghai Province,
446 China (Figure 4) as the case study area ~~to verify the proposed approach through daily~~
447 ~~runoff simulation~~. It is located in a high-altitude, cold and mountainous region with an
448 area of approximately 2,511 km². The average elevation is 3,565 m, and the region
449 features glacier, snow cover and frozen soil.

450 The data used in the case study are listed below. The MERIT DEM with the
451 resolution of 90 m (Yamazaki et al., 2017) was selected for watershed delineation and
452 calculation of terrain attributes. Meteorological data was obtained from the China
453 Meteorological Assimilation Driving Datasets for the SWAT model (CMADS) version

454 1.2, provided in the form of approximately 0.125° resolution gridded station data
455 (Meng et al., 2017). Land cover data was derived from GLOBELAND30 with a
456 resolution of 30 m (<http://www.globallandcover.com>). Soil attribute data was sourced
457 from the Harmonized World Soil Database (HWSD) Version 2.0 (Nachtergaele,
458 2023). The observed daily discharge of the outlet gauge from 2013 to 2018 is obtained
459 from the National Hydrological Yearbook.



460

461 Figure 4. The Babao River watershed and the spatial constitution of the spatially
462 hybrid watershed model.

463 3.2 Experimental design

464 To verify the integration feasibility and simulation effectiveness of the proposed
465 spatially hybrid hydrological modeling approach and its implementation using

466 SEIMS, we constructed one fully-distributed semi-physically-based model structure
467 (section 3.2.1) and one lumped conceptual model structure (section 3.2.2) to build one
468 spatially hybrid model and two spatially consistent models (section 3.2.3) for
469 comparison after parameter calibration (section 3.2.4). It is worth noting that the
470 watershed models constructed in this comparative experiment are not intended to
471 model the hydrological processes in the study precisely, nor to enumerate the possible
472 model structures applicable as illustrated in Figure 1.

473 **3.2.1 The fully-distributed semi-physically-based model structure**

474 The fully-distributed semi-physically-based model structure uses grid cells as the
475 basic simulation units and encompasses simulation algorithms based on physical laws.
476 For instance, the algorithm for percolation is calculated as the product of hydraulic
477 conductivity and the gradient of the hydraulic potential, and the interflow is calculated
478 from the kinematic approximation of Darcy's Law and, with the hydraulic gradient
479 equal to the slope at each grid cell. These two simulation algorithms are the same as
480 those used in WetSpa (Water and Energy Transfer between Soil, Plants and
481 Atmosphere; Liu and Smedt, 2004). Table 1 lists the considered hydrological
482 processes and their simulation algorithms associated with key parameters for
483 calibration. The physically based simulation algorithms primarily utilize spatial
484 parameters with clear physical meaning, such as soil hydraulic conductivity and leaf
485 area index. Besides, this model structure also includes conceptual simulation
486 algorithms such as the surface routing module based on unit hydrograph (Table 1).

487

488 Table 1. Simulation algorithms adopted for the fully-distributed semi-physically-
 489 based model structure and the parameters involved in model calibration

Hydrological process	Simulation algorithm	Parameters involved in calibration
Potential evapotranspiration	Penman-Monteith	K_pet (correction factor)
Interception	Maximum canopy storage	Interc_max (maximum interception storage), Interc_min (minimum interception storage), Pi_b (interception storage capacity exponent)
Glacier	HBV method	-
Snow melt	HBV method	T_rain_snow_delta (rain/snow mixture temperature range)
Infiltration and surface runoff	Modified coefficient method	K_run (runoff exponent), P_max (maximum precipitation corresponding to potential runoff coefficient), Runoff_co (potential runoff coefficient)
Depression	Linsley	Depression (depression storage capacity)
Percolation	Storage routing	-
Interflow	One-dimension kinematic wave	Ki (interflow scale factor)
Actual evaporation	Thornthwaite and Mather method	-
Plant growth	Simplified EPIC	-
Groundwater	Linear reservoir	Base_ex (baseflow recession exponent), df_coef (deep percolation coefficient), gwmax (maximum ground water storage), Kg (baseflow recession coefficient)
Surface routing	Geomorphology-based unit hydrograph	-
Channel routing	Muskingum	MSK_X, MSK_K

490 3.2.2 The lumped conceptual model structure

491 The lumped conceptual model structure adopts DominantHRUs as the simulation
 492 units and GR4J as the main simulation algorithm (Table 2). The Hargreaves method is
 493 used to estimate the potential evapotranspiration for the GR4J. The GR4J receives the

494 potential evapotranspiration and precipitation as input to generate the hillslope runoff
 495 at the outlet of the simulation unit (i.e., DominantHRUs), which implicitly
 496 generalizing the internal surface routing process. The runoff from all DominantHRUs
 497 is then aggregated to the subbasin outlet using a simple accumulation method. The
 498 inter-subbasin channel routing process is modeled using the Muskingum algorithm,
 499 assuming flow transfer only occurs between the outlet points of adjacent upstream-
 500 downstream subbasins. In this case study, each subbasin corresponds to a single
 501 DominantHRU, defined by the land cover and soil type combination that occupies the
 502 largest area within the subbasin. As a result, GR4J can also be applied without an
 503 additional surface routing module.

504

505 Table 2. Simulation algorithms adopted for the lumped conceptual model structure
 506 and the parameters involved in model calibration

Hydrological process	Simulation algorithm	Parameters involved in calibration
Potential evapotranspiration	Hargreaves	-
Surface runoff	GR4J	SOILTHICK, X2, X3, X4
Surface routing	Simple accumulation method	-
Channel routing	Muskingum	MSK_X, MSK_K

507

508 **3.2.3 One spatially hybrid and two spatially consistent model structures for** 509 **comparison**

510 Ideally, physically based models can better simulate hydrological processes with
 511 explicit physical representations. However, due to practical limitations, such as

512 incomplete understanding of hydrological processes and the difficulty of
513 implementing complex simulation algorithms, a conceptual model can serve as a
514 valuable complement. In this case study, we constructed a spatially hybrid model
515 structure (referred to as the HybM; Figure 4) by combining both fully-distributed
516 semi-physically-based (see Section 3.2.1) and lumped conceptual models (see Section
517 3.2.2). We considered the fully-distributed semi-physically-based model structure
518 more suitable for mountainous subbasins (i.e., 13 subbasins shown in Figure 4), while
519 applying the lumped conceptual model structure to gently sloping subbasins (i.e., 16
520 subbasins shown in Figure 4).

521 For comparison with the HybM, we also constructed two spatially consistent
522 model structures: PhyM, which uses only the fully-distributed semi-physically-based
523 model structure, and ConM, which uses only the lumped conceptual model structure.

524 **3.2.4 Comparative experiments**

525 The comparative experiments primarily aim to assess the post-calibration
526 performance of the three watershed model structures. Parameters for model
527 calibration (~~listed in Table 1 and Table 2~~) were chosen through prior sensitivity
528 analyses (listed in Table 1 and Table 2). In principle, the proposed approach adheres to
529 the atomistic forward modeling concept: each subbasin-level model structure is
530 determined based on the appropriate representation of hydrological processes and
531 available data, ensuring a physically reasonable and practically executable watershed
532 model. Ideally, model calibration should utilize multi-scale observations (e.g., at

533 subbasin and watershed outlets) to avoid relying solely on the inverse calibration
534 assumption that successfully watershed-scale reproduction validates subbasin-scale
535 model structures.

536 In the absence of multi-scale observations, it is a common practice in current
537 hydrological modeling to calibrate based solely on the watershed outlet data. In this
538 case study, only the watershed outlet discharge data was available. To partially
539 mitigate this limitation, we designed two calibration strategies (i.e., universal and
540 regional). The universal calibration strategy involves a uniform adjustment of
541 parameters for all subbasin models, while the regional calibration strategy applies
542 separate parameter sets to models of mountainous subbasins and gently sloping
543 subbasins. Consequently, the For HybM, was calibrated using thea regional
544 calibration strategy, while was used: parameters of subbasins with the same model
545 structure (either fully distributed semi-physically based or the lumped conceptual)
546 were adjusted together (i.e., added or multiplied an adjustment value). This means
547 mountainous subbasins shared one set of calibrated parameters, and gently sloping
548 subbasins shared another (Figure 4). To compare with HybM, both PhyM and ConM
549 were calibrated using both universal and regional two strategies: 1) universal
550 calibration, where parameters of all subbasins were adjusted uniformly; and 2)
551 regional calibration, the same strategy used for HybM. All calibration experiments are
552 detailed in (Table 3).

553

554

555 Table 3. Experiments of parameter calibration with different calibration strategies for
 556 different watershed model structures

Calibration strategy	Name of experimental cases		
	ConM	PhyM	HybM
Universal	ConM1	PhyM1	-
Regional	ConM2	PhyM2	HybM

557

558 All three models were executed over a six-year simulation (January 1, 2013 –
 559 December 30, 2018). The first year (2013) served as a warm-up period, followed by a
 560 three-year calibration period (2014–2016) and a two-year validation period (2017–
 561 2018). Model performance was evaluated using three standard indices: the Nash-
 562 Sutcliffe coefficient (NSE; Eq. 1), root mean square error-standard deviation ratio
 563 (RSR; Eq. 2), and percent bias (PBIAS; Eq. 3).

$$NSE = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (1)$$

$$RSR = \frac{\sqrt{\sum_{i=1}^n (O_i - P_i)^2}}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2}} \quad (2)$$

$$PBIAS = \frac{\sum_{i=1}^n (O_i - P_i) \times 100}{\sum_{i=1}^n O_i} \quad (3)$$

564 where O_i and P_i are i -th observed value and predicted value, respectively. \bar{O} is the
 565 averaged observed value, and n is the size of simulated time series.

566 The parameter calibration experiments were conducted using the NSGA-II (non-
 567 dominated sorting genetic algorithm-II; Deb et al., 2002) integrated in the SEIMS
 568 framework (Zhu et al., 2019). The optimization parameters setting for each calibration

569 experiment included a generation of 25 and a population of 360. The multi-objective
570 optimization aimed to maximize NSE and minimize RSR and absolute value of
571 PBIAS. Experiments were carried out on a server equipped with a 2.70 GHz Intel
572 Xeon Gold 6150 dual CPU (36 cores).

573 **3.3 Experimental results and discussion**

574 The successful execution of the constructed spatially hybrid watershed model
575 structure demonstrates the integration feasibility of different subbasin-level model
576 structures in a spatially varying manner. To evaluate the simulation effectiveness of
577 the proposed approach, one set of calibrated parameters of each experiment (detailed
578 in Table S2 of the supplementary material) was selected for comparison, analyzing
579 both model performance metrics and the hydrographs.

580 **3.3.1 Model performance metrics of calibrated model structures**

581 Table 4 lists the model performance metrics for both calibration and validation
582 periods of calibrated model structures under the universal and regional calibration
583 strategies.

584 The spatially consistent fully-distributed semi-physically-based models (PhyM)
585 exhibited similar NSE (~0.59) and RSR (~0.63) in both calibration and validation
586 periods, regardless of the calibration strategy. However, PhyM1 (universal calibration)
587 yielded a lower PBIAS than PhyM2 (regional calibration). While regional calibration
588 generally allows for more flexible parameter adjustments across heterogeneous

589 subbasins, the higher overall bias observed in PhyM2 may be attributed to the lack of
 590 internal subbasin observation data (only outlet discharge was available in this case
 591 study). Without such internal constraints, regional calibration may lead to spatially
 592 inconsistent simulation errors that accumulate toward the watershed outlet, thereby
 593 increasing the overall bias. In contrast, universal calibration often benefits from
 594 compensatory effects among subbasins, resulting in a lower overall bias.

595

596 Table 4. Model performance metrics of calibrated model structures under different
 597 calibration strategies (PhyM1 and PhyM2 represent fully-distributed semi-physically-
 598 based model structure using universal and regional calibration, respectively; ConM1
 599 and ConM2 represent lumped conceptual model structure using universal and regional
 600 calibration, respectively; HybM represents the spatially hybrid model structure using
 601 regional calibration; NSE: Nash-Sutcliffe coefficient; RSR: root mean square error-
 602 standard deviation ratio; PBIAS: percent bias; values are reported as
 603 calibration/validation)

Experimental case	Performance metrics of calibration/validation periods		
	NSE	RSR	PBIAS (%)
PhyM1	0.58/0.60	0.64/0.63	10.63/2.58
PhyM2	0.59/0.60	0.64/0.63	17.34/13.90
ConM1	0.41/0.32	0.77/0.82	2.89/-42.87
ConM2	0.45/0.50	0.74/0.71	10.96/-21.03
HybM	0.72/0.60	0.53/0.63	10.02/-18.28

604

605 Unlike the effect of calibration strategies on PhyM, the spatially consistent
 606 lumped conceptual models (ConM) showed moderate improvements under the
 607 regional calibration strategy (ConM2) compared to the universal calibration strategy
 608 (ConM1). Specifically, for calibration/validation, the NSE increased from 0.41/0.32 to

609 0.45/0.50 and the RSR decreased from 0.77/0.82 to 0.74/0.71. For PBIAS, ConM2
610 yielded 10.96%/-21.03%, showing improved validation bias compared to ConM1
611 (2.89%/-42.87%), despite a higher calibration-period bias. Conceptual models like
612 ConM, with simple model structure and few parameters, are often considered easier to
613 calibrate and potentially perform better under regional calibration. However, in this
614 study, both ConM1 and ConM2 exhibited relatively low NSE and high RSR values in
615 both periods, indicating that the GR4J-based conceptual model structure has limited
616 ability to represent the hydrological processes in this watershed. The noticeable
617 decline in validation performance for both ConM1 and ConM2 (e.g., the substantial
618 shift in PBIAS from overestimation to underestimation) further reflects the limited
619 generalization of ConM. The contrasting results between ConM and PhyM may be
620 attributed to their structural differences in handling spatial variability. ConM relies
621 more on regional calibration to consider spatial heterogenous across subbasins by
622 adjusting its less physically constrained parameters. In contrast, PhyM captures spatial
623 heterogeneity directly through spatially distributed input data and parameters,
624 implying a low dependency on calibration strategies to represent spatial variations in
625 hydrological processes.

626 The spatially hybrid model structure (HybM) demonstrated a balanced model
627 performance by leveraging the strengths of both PhyM and ConM, achieving the
628 highest NSE (0.72/0.60) and lowest RSR (0.53/0.63) among all experimental cases.
629 However, its PBIAS (10.02%/-18.28%) was lower than (i.e., better overall bias) that

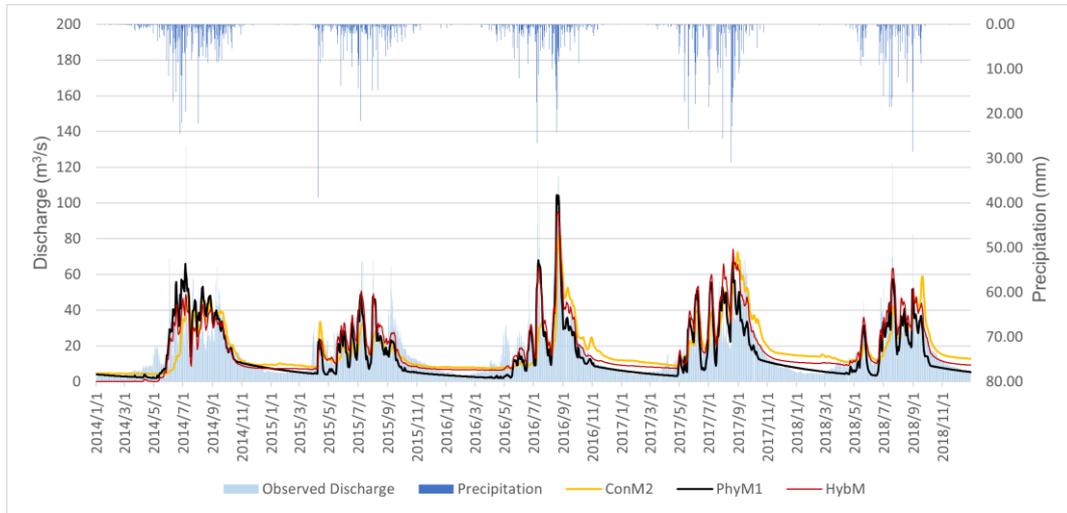
630 of both ConM cases but higher than (i.e., worse overall bias) both PhyM cases. This
631 reflects that the spatially hybrid model structure provides a promising compromise
632 between modeling flexibility and simulation accuracy. That is, while HybM combined
633 the calibration responsiveness of ConM and the process realism of PhyM, it also
634 inherited some of their respective limitations, such as bias associated with the
635 conceptual representation. Overall, these findings highlight the importance of careful
636 model structure construction and the necessity of multi-site and long-term observation
637 data to effectively constrain calibration and fully realize the benefits of the proposed
638 approach.

639 **3.3.2 Hydrographs of calibrated model structures**

640 Figure 5 compares the outlet hydrographs simulated by PhyM1, ConM2, and
641 HybM against the observed discharge.

642 During the dry seasons (typically November to April), when baseflow dominates
643 streamflow, PhyM1 accurately simulates baseflow magnitudes, benefiting from its
644 process-based representation of hydrological processes. In contrast, ConM2 tends to
645 overestimate baseflow, likely due to its simplified recession formulation and lack of
646 explicit representation of groundwater storage and release dynamics. During the wet
647 season, characterized by high-intensity precipitation events, PhyM1 produces sharper
648 rising and falling limbs, closely matching observed peaks and recessions. This
649 behavior reflects the physical realism of PhyM in representing rapid surface and
650 subsurface responses in the study area. Conversely, ConM2 often either overestimates

651 or underestimates peak flows, likely due to limitations in its conceptual routing and
652 storage structure.



653
654 Figure 5. Simulated outlet hydrographs of best-performing cases for each model
655 structure: PhyM1 (fully-distributed semi-physically-based model structure using
656 universal calibration strategy), ConM2 (lumped conceptual model structure using
657 regional calibration strategy), and HybM (spatially hybrid model structure using
658 regional calibration strategy)

659
660 The spatially hybrid model (HybM) integrates the strengths of both model
661 structures. HybM more accurately captures peak magnitudes and recession processes
662 throughout the simulation period, exhibiting rising limbs similar to PhyM1 and a
663 moderated baseflow response that is less overestimated than in ConM2. Although
664 HybM still overestimates baseflow compared to observations, its improved flood
665 response and recession simulation suggest a more balanced simulation across different
666 hydrological conditions.

667 Overall, these results illustrate the benefits of spatially combining different
668 model structures. The proposed approach offers enhanced flexibility to accommodate

669 diverse application contexts and demonstrates promising improvements in general
670 hydrograph accuracy.

671 **4 Discussion**

672 The case study results have demonstrated the integration feasibility and
673 simulation effectiveness of the proposed spatially hybrid hydrological modeling
674 approach. This section further discusses its broader implications, focusing on the
675 significance of the spatially hybrid modeling approach, the advantages of SEIMS in
676 implementing the proposed approach, and limitations and future directions.

677 **4.1 Significance of the spatially hybrid modeling approach**

678 The case study results confirmed the methodological validity of spatially
679 combining different model structures within a watershed. The spatially hybrid model
680 structure (HybM) constructed in this case study achieved highest performance in
681 terms of NSE and RSR. However, it also inherited limitations from its constituent
682 model structures, such as higher PBIAS from the lumped conceptual model structure
683 (ConM). This reflects an inherent trade-off in spatially hybrid modeling, that is,
684 enhanced flexibility and local adaptability often come at the cost of increased
685 structural complexity and potential uncertainty. Despite these limitations, the
686 proposed approach offers a practical and adaptable framework to address spatial
687 heterogeneity in diverse hydrological modeling application contexts, particularly
688 where data availability and watershed characteristics vary across space.

689 It should be noted that this case study was designed primarily to demonstrate
690 methodological feasibility, relying on a simplified application context and data-driven
691 model calibration. Future research should place more emphasis on integrating domain
692 knowledge-driven with data-driven methods to formalize complex application
693 contexts. This will help in identifying appropriate spatially hybrid model structures,
694 and constraining model calibration using expert knowledge, ~~and~~ modeling experience
695 from similar case studies, and multi-scale observation data (Qin et al., 2025).

696 **4.2 Advantages of SEIMS in implementing the proposed** 697 **approach**

698 SEIMS effectively supports the implementation of the spatially hybrid
699 modeling approach through its modular and subbasin-independent architecture,
700 offering both modeling flexibility and computational efficiency.

701 SEIMS's design enables model developers to reuse or adapt existing model
702 codes as SEIMS modules to simulate individual or multiple hydrological processes.
703 For instance, the GR4J module was adapted from the Raven framework (Craig, 2020).
704 Newly developed modules can be flexibly combined with existing ones to construct
705 various model structures. This capability is particularly valuable for large and
706 heterogeneous watersheds where modeling application contexts vary across regions.
707 For instance, in subbasins with limited spatial data, lumped conceptual components
708 can be employed in place of data-intensive distributed model structures to ensure
709 model feasibility. It is worth noting that while SEIMS provides this flexibility, module

710 developers are responsible for specifying input requirements and boundary conditions
711 for their modules, and users should assess the hydrological rationality and integration
712 feasibility of their combined model structure.

713 Regarding computational efficiency, in the case study, the fully-distributed
714 semi-physically-based model structure required approximately 75 hours to complete
715 9000 model runs for the calibration experiment, whereas the lumped conceptual
716 model structure took only about 1 hour. The spatially hybrid model, incorporating
717 both structures, achieved a balanced efficiency of around 30 hours. This
718 computational efficiency, enabled by the parallelization strategies of SEIMS, supports
719 more scalable applications in large watersheds, particularly those involving extensive
720 model runs such as uncertainty analysis, parameter calibration, and scenario analysis.

721 **4.3 Limitations and future directions**

722 While Section 4.1 and 4.2 have discussed the significance of the proposed
723 approach and the advantages of its SEIMS implementation, this section highlights key
724 limitations and outlines future directions to enhance its practical applicability.

725 First, the successful application of the current implementation largely depends
726 on the breadth and quality of the SEIMS module library. Though extensible, the
727 module library lacks modules for several critical hydrological processes (e.g., frozen
728 soil dynamics) and specific representations (e.g., fully-physically-based simulation
729 algorithms that tightly couple hillslope hydrological processes). Recent research
730 efforts continue to expand SEIMS module library to support more complex

731 hydrological processes, for instance, by modeling groundwater–surface water
732 interactions between alpine runoff and alluvial aquifers in high mountain watersheds
733 (Liu et al., 2025). We plan to gradually implement a variety of fully-physically-based
734 simulation modules, such as a 2D hillslope overland flow module inspired by
735 FullSWOF (Full Shallow-Water equations for Overland Flow; Delestre et al., 2017),
736 and a fully coupled 3D module of overland flow, subsurface flow, and groundwater
737 flow following approaches from SHUD (Shu et al., 2020) and ParFlow (Kollet and
738 Maxwell, 2006). We encourage model developers to contribute to the enrichment of
739 the SEIMS module library, either by transplanting existing code or developing new
740 modules based on established hydrological equations and the SEIMS module
741 template.

742 Second, while the subbasin-independent architecture of SEIMS is a key feature
743 to implement the proposed approach, it also raises concerns about inter-subbasin
744 connectivity for more complex modeling circumstances. For instance, when multiple
745 flow direction algorithms are used to construct the hillslope flow routing network,
746 flow paths may cross subbasin boundaries and the connectivity between subbasins
747 becomes more frequent than only connected by channel network. Future work should
748 explore flexible inter-subbasin connectivity mechanisms to consider more realistic
749 hydrological interactions across subbasins. Besides, while the inter-subbasin coupling
750 operates at a consistent subbasin scale through the same or different channel routing
751 algorithms, this study did not explicitly address the coupling of processes across

752 nested spatial and temporal scales within each subbasin and the transfer of
753 uncertainties between them, which remains central challenges in hydrology
754 community. The proposed approach and the implemented modeling framework are
755 extensible to support such research when new theories and data become available.

756 Third, while the proposed approach enables flexible configuration of model
757 structure across subbasins, it currently lacks intelligent methods and tools to reduce
758 the substantial modeling burdens on users (particularly non-expert users), when
759 constructing appropriate model structures for specific application contexts. Future
760 efforts should focus on developing domain knowledge-driven methods that
761 incorporate various knowledge types, such as: (1) integration knowledge of SEIMS
762 modules derived from module metadata; (2) rule-based relationships linking
763 application contexts (e.g., watershed topographic characteristics and available data) to
764 suitable simulation algorithms; and (3) case-based reasoning to determine appropriate
765 simulation units, algorithms, and parameter settings (Jiang et al., 2019; Qin et al.,
766 2025).

767 Fourth, ~~while~~ the current case study was designed as a simplified proof-of-
768 concept application is sufficient to demonstrate the integration feasibility and
769 simulation effectiveness of the proposed approach, ~~its application context remains~~
770 relatively simplified. Nevertheless, m More comprehensive case studies in watershed
771 with multi-scale observed data and ~~across~~ diverse watersheds (e.g., with varying
772 climatic, topographic, and ~~data-landuse~~ conditions) are needed to further evaluate the

773 robustness, generalizability, and uncertainty implications of the ~~spatially hybrid-~~
774 ~~modelingproposed~~ approach. For instance, future applications should incorporate
775 uncertainty analysis frameworks to better understand and quantify the trade-offs
776 between modeling flexibility and simulation accuracy.

777 **5 Conclusion**

778 This study proposed a new spatially hybrid hydrological modeling approach to
779 address the challenge of representing spatial heterogeneity in complex watersheds.
780 Adopting a divide-and-conquer strategy, the approach allows for flexible combination
781 of compatible spatial discretization schemes (i.e., simulation units) and hydrological
782 process representations (i.e., simulation algorithms) across subbasins. This approach
783 provides a pragmatic and flexible modeling solution under the current lack of
784 generally accepted theory for hydrological scaling issues, enabling the integration of
785 existing hydrological modeling methods at the subbasin scale.

786 The approach was implemented within the SEIMS ~~hydrological modeling-~~
787 framework, leveraging its modular, subbasin-independent architecture and parallel
788 computing capabilities. Comparative experiments in a medium-sized watershed
789 demonstrated the integration feasibility and simulation effectiveness of the proposed
790 approach. ~~T~~Specifically, the spatially hybrid model structure successfully combines
791 the strengths of both spatially consistent model structures, achieving improved
792 general performance. ~~W~~hile ~~the hybrid model structure~~ also ~~inherently~~ inheriting
793 some limitations from its constituent components (e.g., simulation bias from the

794 conceptual model structure). The experimental results highlight its capability to
795 balance modeling flexibility and simulation accuracy under heterogeneous watershed
796 conditions.

797 This study does not intend to resolve the fundamental hydrological scaling
798 issues, nor to ignore their existence, but rather to provide ~~The proposed approach~~
799 ~~offers~~ a practical and extensible framework for hydrological modeling across diverse
800 application contexts. The proposed approach and its implementation are extensible,
801 through ~~By enabling~~ the reuse and integration of existing model efforts, thus
802 holding the potential to support investigations into these theoretical issues as new
803 theories and data become available ~~the proposed approach facilitates efficient model~~
804 ~~development and customization.~~ Moreover ~~Moreover~~, this study lays the groundwork
805 for future research on knowledge-driven intelligent modeling methods and tools for
806 complex watershed modeling and management in spatially heterogeneous
807 environments.

808

809 **Acknowledgments**

810 This work was supported by National Natural Science Foundation of China
811 [42101480, 42471499], National Key Research and Development Program of China
812 [2021YFB3900904], and LREIS [YPI005, KPI003]. We would likewant to
813 acknowledge Dr. Kaiwen Wang from the IGSNRR, CAS, for his valuable
814 discussions on regarding the physically-based hydrological modeling ~~with Dr. Kaiwen~~

815 Wang from the IGSNRR, CAS. We thank the anonymous reviewers for their
816 insightful comments on the definition of physically-based models and hydrological
817 scale-related issues, which enriched this work and inspired future research directions.

818 **Declarations of interest:** none.

819 **Reference**

820 Abbott, M.B., Bathurst, J.C., Cunge, J.A., O’Connell, P.E., Rasmussen, J., 1986. An
821 introduction to the European Hydrological System — Systeme Hydrologique
822 Europeen, “SHE”, 2: Structure of a physically-based, distributed modelling
823 system. Journal of Hydrology 87, 61–77. [https://doi.org/10.1016/0022-](https://doi.org/10.1016/0022-1694(86)90115-0)
824 [1694\(86\)90115-0](https://doi.org/10.1016/0022-1694(86)90115-0)

825 Arnold, J. G., Allen, P. M., Volk, M., Williams, J. R., & Bosch, D. D., 2010.
826 Assessment of different representations of spatial variability on SWAT model
827 performance. Transactions of the ASABE 53, 1433–1443.
828 <https://doi.org/10.13031/2013.34913>

829 Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large Area
830 Hydrologic Modeling and Assessment Part I: Model Development. JAWRA
831 Journal of the American Water Resources Association 34, 73–89.
832 <https://doi.org/10.1111/j.1752-1688.1998.tb05961.x>

833 Beven, K.J., 2000. Uniqueness of place and process representations in hydrological
834 modelling. Hydrology and Earth System Sciences 4, 203–213.
835 <https://doi.org/10.5194/hess-4-203-2000>

836 Beven, K.J., 2012. Rainfall-runoff modelling: the primer, 2nd ed. ed. Wiley-
837 Blackwell, Chichester, West Sussex; Hoboken, NJ.

838 Beven, K., 1989. Changing ideas in hydrology — The case of physically-based
839 models. Journal of Hydrology 105, 157–172. [https://doi.org/10.1016/0022-](https://doi.org/10.1016/0022-1694(89)90101-7)
840 [1694\(89\)90101-7](https://doi.org/10.1016/0022-1694(89)90101-7)

841 Beven, K.J., Kirkby, M.J., 1979. A physically based, variable contributing area model
842 of basin hydrology. Hydrological Sciences Bulletin 24, 43–69.
843 <https://doi.org/10.1080/02626667909491834>

844 Butts, M.B., Payne, J.T., Kristensen, M., Madsen, H., 2004. An evaluation of the
845 impact of model structure on hydrological modelling uncertainty for streamflow
846 simulation. Journal of Hydrology 298, 242–266.
847 <https://doi.org/10.1016/j.jhydrol.2004.03.042>

848 Chow, V.T., Maidment, D.R., Mays, L.W., 1988. Applied hydrology, 2nd ed.
849 McGraw-Hill, New York.

850 Clark, M.P., Kavetski, D., Fenicia, F., 2011. Pursuing the method of multiple working
851 hypotheses for hydrological modeling. Water Resources Research 47.
852 <https://doi.org/10.1029/2010WR009827>

853 Clark, M.P., Nijssen, B., Lundquist, J.D., Kavetski, D., Rupp, D.E., Woods, R.A.,
854 Freer, J.E., Gutmann, E.D., Wood, A.W., Brekke, L.D., Arnold, J.R., Gochis,
855 D.J., Rasmussen, R.M., 2015. A unified approach for process-based hydrologic
856 modeling: 1. Modeling concept. Water Resources Research 51, 2498–2514.

857 <https://doi.org/10.1002/2015WR017198>

858 Coron, L., Thirel, G., Delaigue, O., Perrin, C., Andréassian, V., 2017. The suite of
859 lumped GR hydrological models in an R package. *Environmental Modelling &*
860 *Software* 94, 166–171. <https://doi.org/10.1016/j.envsoft.2017.05.002>

861 Craig, J.R., 2020. Flexible watershed simulation with the Raven hydrological
862 modelling framework. *Environmental Modelling & Software* 129, 104728.

863 David, P.C., Chaffe, P.L.B., Chagas, V.B.P., Dal Molin, M., Oliveira, D.Y., Klein,
864 A.H.F., Fenicia, F., 2022. Correspondence Between Model Structures and
865 Hydrological Signatures: A Large-Sample Case Study Using 508 Brazilian
866 Catchments. *Water Resources Research* 58, e2021WR030619.
867 <https://doi.org/10.1029/2021WR030619>

868 Deb K, Pratap A, Agarwal S, et al., 2002. A fast and elitist multiobjective genetic
869 algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation* 6: 182–
870 197.

871 Dehotin, J., Braud, I., 2008. Which spatial discretization for distributed hydrological
872 models? Proposition of a methodology and illustration for medium to large-scale
873 catchments. *Hydrology and Earth System Sciences* 12, 769–796.
874 <https://doi.org/10.5194/hess-12-769-2008>

875 [Delestre, O., Darboux, F., James, F., Lucas, C., Laguerre, C., Cordier, S., 2017.](#)
876 [FullSWOF: Full Shallow-Water equations for Overland Flow. *Journal of Open*](#)
877 [Source Software 2, 448. <https://doi.org/10.21105/joss.00448>](#)

878 Dile, Y.T., Daggupati, P., George, C., Srinivasan, R., Arnold, J., 2016. Introducing a
879 new open source GIS user interface for the SWAT model. *Environmental*
880 *Modelling & Software* 85, 129–138.
881 <https://doi.org/10.1016/j.envsoft.2016.08.004>

882 Dingman, S.L., 2015. *Physical hydrology*, 3rd ed. Waveland Press, Inc, Long Grove,
883 Illinois.

884 [Dooge, J.C.I., 1986. Looking for hydrologic laws. *Water Resources Research* 22, 46S-](https://doi.org/10.1029/WR022i09Sp0046S)
885 [58S. https://doi.org/10.1029/WR022i09Sp0046S](https://doi.org/10.1029/WR022i09Sp0046S)

886 Fenicia, F., Kavetski, D., Savenije, H.H.G., 2011. Elements of a flexible approach for
887 conceptual hydrological modeling: 1. Motivation and theoretical development.
888 *Water Resources Research* 47. <https://doi.org/10.1029/2010WR010174>

889 Fenicia, F., Kavetski, D., Savenije, H.H.G., 2011. Elements of a flexible approach for
890 conceptual hydrological modeling: 1. Motivation and theoretical development.
891 *Water Resources Research* 47. <https://doi.org/10.1029/2010WR010174>

892 Fenicia, F., Kavetski, D., Savenije, H.H.G., Pfister, L., 2016. From spatially variable
893 streamflow to distributed hydrological models: Analysis of key modeling
894 decisions. *Water Resources Research* 52, 954–989.
895 <https://doi.org/10.1002/2015WR017398>

896 Gao, H., Hrachowitz, M., Fenicia, F., Gharari, S., Savenije, H.H.G., 2014. Testing the
897 realism of a topography-driven model (FLEX-Topo) in the nested catchments of
898 the Upper Heihe, China. *Hydrology and Earth System Sciences* 18, 1895–1915.

899 <https://doi.org/10.5194/hess-18-1895-2014>

900 Gharari, S., Gupta, H.V., Clark, M.P., Hrachowitz, M., Fenicia, F., Matgen, P.,
901 Savenije, H.H.G., 2021. Understanding the Information Content in the Hierarchy
902 of Model Development Decisions: Learning From Data. *Water Resources*
903 *Research* 57, e2020WR027948. <https://doi.org/10.1029/2020WR027948>

904 Gunduz, O., Aral, M., 2005. Large-Scale Hybrid Watershed Modeling, in: Frevert, D.,
905 Singh, V. (Eds.), *Watershed Models*. CRC Press, pp. 74–95.
906 <https://doi.org/10.1201/9781420037432.ch4>

907 Harpham, Q.K., Hughes, A., Moore, R.V., 2019. Introductory overview: The OpenMI
908 2.0 standard for integrating numerical models. *Environmental Modelling &*
909 *Software* 122, 104549. <https://doi.org/10.1016/j.envsoft.2019.104549>

910 Hill, C., DeLuca, C., Balaji, Suarez, M., Da Silva, A., 2004. The architecture of the
911 earth system modeling framework. *Computing in Science & Engineering* 6, 18–
912 28. <https://doi.org/10.1109/MCISE.2004.1255817>

913 Hrachowitz, M., Clark, M.P., 2017. HESS Opinions: The complementary merits of
914 competing modelling philosophies in hydrology. *Hydrology and Earth System*
915 *Sciences* 21, 3953–3973. <https://doi.org/10.5194/hess-21-3953-2017>

916 Jiang, J., Zhu, A.-X., Qin, C.-Z., Liu, J., 2019. A knowledge-based method for the
917 automatic determination of hydrological model structures. *Journal of*
918 *Hydroinformatics* 21, 1163–1178. <https://doi.org/10.2166/hydro.2019.029>

919 Kiraz, M., Coxon, G., Wagener, T., 2023. A priori selection of hydrological model

920 structures in modular modelling frameworks: application to Great Britain.
921 Hydrological Sciences Journal 68, 2042–2056.
922 <https://doi.org/10.1080/02626667.2023.2251968>

923 Kneis, D., 2015. A lightweight framework for rapid development of object-based
924 hydrological model engines. Environmental Modelling & Software 68, 110–121.
925 <https://doi.org/10.1016/j.envsoft.2015.02.009>

926 Knoben, W.J.M., Freer, J.E., Fowler, K.J.A., Peel, M.C., Woods, R.A., 2019. Modular
927 Assessment of Rainfall–Runoff Models Toolbox (MARRMoT) v1.2: an open-
928 source, extendable framework providing implementations of 46 conceptual
929 hydrologic models as continuous state-space formulations. Geoscientific Model
930 Development 12, 2463–2480. <https://doi.org/10.5194/gmd-12-2463-2019>

931 Knoben, W.J.M., Freer, J.E., Peel, M.C., Fowler, K.J.A., Woods, R.A., 2020. A Brief
932 Analysis of Conceptual Model Structure Uncertainty Using 36 Models and 559
933 Catchments. Water Resources Research 56, e2019WR025975.
934 <https://doi.org/10.1029/2019WR025975>

935 [Kollet, S.J., Maxwell, R.M., 2006. Integrated surface–groundwater flow modeling: A](#)
936 [free-surface overland flow boundary condition in a parallel groundwater flow](#)
937 [model. Advances in Water Resources 29, 945–958.](#)
938 <https://doi.org/10.1016/j.advwatres.2005.08.006>

939 Ley, R., Hellebrand, H., Casper, M.C., Fenicia, F., 2016. Is **C**atchment
940 **C**lassification **P**ossible by **M**means of **m**Multiple **m**Model **s**Structures? A Case

941 Study Based on 99 Catchments in Germany. Hydrology 3, 22.
942 <https://doi.org/10.3390/hydrology3020022>

943 Li, X., Zhang, L., Zheng, Y., Yang, D., Wu, F., Tian, Y., Han, F., Gao, B., Li, H.,
944 Zhang, Y., Ge, Y., Cheng, G., Fu, B., Xia, J., Song, C., Zheng, C., 2021. Novel
945 hybrid coupling of ecohydrology and socioeconomy at river basin scale: A
946 watershed system model for the Heihe River basin. Environmental Modelling &
947 Software 141, 105058. <https://doi.org/10.1016/j.envsoft.2021.105058>

948 Lindström, G., Johansson, B., Persson, M., Gardelin, M., Bergström, S., 1997.
949 Development and test of the distributed HBV-96 hydrological model. Journal of
950 Hydrology 201, 272–288. [https://doi.org/10.1016/S0022-1694\(97\)00041-3](https://doi.org/10.1016/S0022-1694(97)00041-3)

951 Liu, Jiaojiao, Liu, Junzhi, Liu, M., Tian, S., Liu, Yongbo, Yang, W., Liu, Yonqin,
952 2025. Development of an alpine hydrological model considering the recharge of
953 stream water to alluvial plain aquifers. Environmental Modelling & Software
954 192, 106567. <https://doi.org/10.1016/j.envsoft.2025.106567>

955 Liu, J., Liu, Z., Yin, Y., Croke, B. F. W., Chen, M., Qin, C.-Z., Tang, G., Zhu, A.-X.,
956 2021. A hybrid vector-raster approach to drainage network construction in
957 agricultural watersheds with rice terraces and ponds. Journal of Hydrology 601,
958 126585. <https://doi.org/10.1016/j.jhydrol.2021.126585>

959 [Liu, Y., De Smedt, F., 2004. WetSpa extension, a GIS-based hydrologic model for](#)
960 [flood prediction and watershed management. Vrije Universiteit Brussel, Brussel,](#)
961 [Belgium.](#)

962 Liu, J., Zhu, A.-X., Qin, C.-Z., Wu, H., Jiang, J., 2016. A two-level parallelization
963 method for distributed hydrological models. Environmental Modelling &
964 Software 80, 175–184. <https://doi.org/10.1016/j.envsoft.2016.02.032>

965 Liu, J., Zhu, A.-X., Liu, Y., Zhu, T., Qin, C.-Z., 2014. A layered approach to parallel
966 computing for spatially distributed hydrological modeling. Environmental
967 Modelling & Software 51, 221–227.
968 <https://doi.org/10.1016/j.envsoft.2013.10.005>

969 Liu, Y., Zhang, K., Li, Z., Liu, Z., Wang, J., Huang, P., 2020. A hybrid runoff
970 generation modelling framework based on spatial combination of three runoff
971 generation schemes for semi-humid and semi-arid watersheds. Journal of
972 Hydrology 590, 125440. <https://doi.org/10.1016/j.jhydrol.2020.125440>

973 [Meng, X., Wang, H., 2017. Significance of the China meteorological assimilation](#)
974 [driving datasets for the SWAT model \(CMADS\) of East Asia. Water, 9\(10\), 765.](#)
975 <https://doi.org/10.3390/w9100765>

976 Milad₂ J., Sobri₂ H., Mohsen₂ S., 2012. A Review on Theoretical Consideration and
977 Types of Models in Hydrology. Journal of Environmental Science and
978 Technology 5: 249–261.

979 Nachtergaele, F., van Velthuisen, H., Verelst, L., Wiberg, D., Henry, M., Chiozza, F.,
980 Yigini, Y., Aksoy, E., Batjes, N., Boateng, E., others, 2023. Harmonized world
981 soil database version 2.0. Food and Agriculture Organization of the United
982 Nations.

983 Perrin, C., Michel, C., Andréassian, V., 2003. Improvement of a parsimonious model
984 for streamflow simulation. *Journal of Hydrology* 279, 275–289.
985 [https://doi.org/10.1016/S0022-1694\(03\)00225-7](https://doi.org/10.1016/S0022-1694(03)00225-7)

986 Pilz, T., Francke, T., Baroni, G., Bronstert, A., 2020. How to Tailor My Process-Based
987 Hydrological Model? Dynamic Identifiability Analysis of Flexible Model
988 Structures. *Water Resources Research* 56, e2020WR028042.
989 <https://doi.org/10.1029/2020WR028042>

990 Qin, C.-Z., Zhu, L.-J., Zhu, A.-X., 2025. Position paper: Domain knowledge-driven
991 intelligentization of watershed modeling and scenario analysis for precise
992 watershed management. *Information Geography* 1, 100016.
993 <https://doi.org/10.1016/j.infgeo.2025.100016>

994 Savenije, H.H.G., 2010. HESS Opinions “Topography driven conceptual modelling
995 (FLEX-Topo).” *Hydrology and Earth System Sciences* 14, 2681–2692.
996 <https://doi.org/10.5194/hess-14-2681-2010>

997 Savenije, H.H.G., 2009. HESS Opinions “The art of hydrology.” *Hydrology and Earth
998 System Sciences* 13, 157–161. <https://doi.org/10.5194/hess-13-157-2009>

999 [Shu, L., Ullrich, P.A., Duffy, C.J., 2020. Simulator for Hydrologic Unstructured](https://doi.org/10.5194/gmd-13-2743-2020)
1000 [Domains \(SHUD v1.0\): numerical modeling of watershed hydrology with the](https://doi.org/10.5194/gmd-13-2743-2020)
1001 [finite volume method. *Geoscientific Model Development* 13, 2743–2762.](https://doi.org/10.5194/gmd-13-2743-2020)
1002 <https://doi.org/10.5194/gmd-13-2743-2020>

1003 Sidle, R.C., 2021. Strategies for smarter catchment hydrology models: incorporating

1004 scaling and better process representation. *Geoscience Letters* 8, 24.
1005 <https://doi.org/10.1186/s40562-021-00193-9>

1006 [Sivapalan, M., Blöschl, G., Zhang, L., Vertessy, R., 2003. Downward approach to](#)
1007 [hydrological prediction. *Hydrological Processes* 17, 2101–2111.](#)
1008 <https://doi.org/10.1002/hyp.1425>

1009 Sui, D., Turner, M, 2022. General theories and principles in geography and
1010 GIScience: Moving beyond the idiographic and nomothetic dichotomy. *Annals*
1011 *of GIS*, 28, 1–4. <https://doi.org/10.1080/19475683.2022.2030939>

1012 Tague, C.L., Band, L.E., 2004. RHESys: Regional Hydro-Ecologic Simulation
1013 System—An Object-Oriented Approach to Spatially Distributed Modeling of
1014 Carbon, Water, and Nutrient Cycling. *Earth Interactions* 8, 1–42.
1015 [https://doi.org/10.1175/1087-3562\(2004\)8<1:RRHSSO>2.0.CO;2](https://doi.org/10.1175/1087-3562(2004)8<1:RRHSSO>2.0.CO;2)

1016 [Tang, G., Li, S., Yang, M., Xu, Z., Liu, Y., Gu, H., 2019. Streamflow response to snow](#)
1017 [regime shift associated with climate variability in four mountain watersheds in](#)
1018 [the US Great Basin. *Journal of Hydrology* 573, 255–266.](#)
1019 <https://doi.org/10.1016/j.jhydrol.2019.03.021>

1020 Teshager, A. D., Gassman, P. W., Secchi, S., Schoof, J. T., & Misgna, G., 2016.
1021 Modeling agricultural watersheds with the soil and water assessment tool
1022 (SWAT): Calibration and validation with a novel procedure for spatially explicit
1023 HRUs. *Environmental Management* 57, 894–911.
1024 <https://doi.org/10.1007/s00267-015-0636-4>

1025 Thébault, C., Perrin, C., Andréassian, V., Thirel, G., Legrand, S., Delaigue, O., 2023.
1026 Multi-model approach in a variable spatial framework for streamflow simulation.
1027 EGU sphere. <https://doi.org/10.5194/egusphere-2023-569>

1028 van Esse, W.R., Perrin, C., Booij, M.J., Augustijn, D.C.M., Fenicia, F., Kavetski, D.,
1029 Lobligeois, F., 2013. The influence of conceptual model structure on model
1030 performance: a comparative study for 237 French catchments. Hydrology and
1031 Earth System Sciences 17, 4227–4239. [https://doi.org/10.5194/hess-17-4227-](https://doi.org/10.5194/hess-17-4227-2013)
1032 2013

1033 Wagener, T., Boyle, D.P., Lees, M.J., Wheater, H.S., Gupta, H.V., Sorooshian, S.,
1034 2001. A framework for development and application of hydrological models.
1035 Hydrology and Earth System Sciences 5, 13–26. [https://doi.org/10.5194/hess-5-](https://doi.org/10.5194/hess-5-13-2001)
1036 13-2001

1037 Wang, J., Chen, M., Lü, G., Yue, S., Wen, Y., Sheng, Y., Lu, M., 2021a. A construction
1038 method of visual conceptual scenario for hydrological conceptual modeling.
1039 Environmental Modelling & Software 145, 105190.
1040 <https://doi.org/10.1016/j.envsoft.2021.105190>

1041 Wang, C., Hua, W., Chen, G., Fang, X., Li, X., 2021b. Distributed-Framework Basin
1042 Modeling System: I. Overview and Model Coupling. Water 13, 678.
1043 <https://doi.org/10.3390/w13050678>

1044 Wigmosta, M.S., Vail, L.W., Lettenmaier, D.P., 1994. A distributed hydrology-
1045 vegetation model for complex terrain. Water Resources Research 30, 1665–1679.

1046 Yamazaki, D., Ikeshima, D., Tawatari, R., Yamaguchi, T., O'Loughlin, F., Neal, J. C.,
1047 et al., 2017. A high - accuracy map of global terrain elevations. Geophysical
1048 Research Letters 44, 5844 - 5853. <https://doi.org/10.1002/2017GL072874>

1049 Zhu, L.-J., Liu, J., Qin, C.-Z., Zhu, A.-X., 2019. A modular and parallelized watershed
1050 modeling framework. Environmental Modelling & Software 122, 104526.
1051 <https://doi.org/10.1016/j.envsoft.2019.104526>
1052