

1 **Spatially hybrid hydrological modeling based on spatial**
2 **heterogeneity of watershed characteristics**

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4 **Yu-Jing Wang^{a,b}, Liang-Jun Zhu^{a,b,*}, Cheng-Zhi Qin^{a,b,c,d,*}, A-Xing Zhu^{a,b,d,e,f}**

5 ^a State Key Laboratory of Resources and Environmental Information System, Institute of
6 Geographic Sciences and Natural Resources Research, CAS, Beijing, China

7 ^b College of Resources and Environment, University of Chinese Academy of Sciences,
8 Beijing, China

9 ^c School of Geography and Tourism, Shaanxi Normal University, Xi'an, China

10 ^d Jiangsu Center for Collaborative Innovation in Geographical Information Resource
11 Development and Application, Nanjing, China

12 ^e Department of Geography, University of Wisconsin-Madison, Madison, WI, USA

13 ^f Key Laboratory of Virtual Geographic Environment (Ministry of Education of PRC),
14 Nanjing Normal University, Nanjing, China

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17 Corresponding author: Liang-Jun Zhu and Cheng-Zhi Qin

18 E-mail addresses: zlj@lreis.ac.cn and qincz@lreis.ac.cn

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1 **Abstract:**

2 Hydrological modeling with a uniform model structure is often unreasonable for
3 complex watersheds with significant spatial heterogeneity. For such a situation, a
4 reasonable way is to integrate multiple hydrological model structures, each tailored to
5 a specific area in the watershed of interest. While some pioneering hydrological
6 modeling frameworks have enabled such integration of different hydrological model
7 structures, they have primarily focused on lumped and conceptual models. The
8 absence of distributed and physically-based models in such integration limits the
9 capabilities of those frameworks to represent the spatially heterogeneous hydrological
10 processes in detail. This paper proposes an innovative spatially hybrid hydrological
11 modeling approach based on a divide-and-conquer idea. In this approach, the
12 watershed is initially divided into model structure allocation units (MSAUs) at the
13 subbasin level. Individual model structure can be flexibly composed of conventional
14 conceptual and physically-based models, and then allocated to MSAU deemed
15 suitable. Finally, these model structures at MSAU level are integrated into a spatially
16 hybrid watershed model. The proposed approach is implemented through extending
17 the Spatially Explicit Integrated Modeling System (SEIMS). A case study was
18 conducted in a medium-sized natural watershed in Heihe River Basin, China, where
19 two distinct model structures, containing the components from both lumped
20 conceptual model and distributed physically-based model, were integrated into a
21 spatially hybrid model, so to evaluate the effectiveness of the proposed approach. The
22 results demonstrate that the spatially hybrid hydrological model integrated using the
23 proposed approach could harness the strengths of both model structures on the
24 simulation performance. This approach holds promise for improving the rationality of
25 hydrological modeling in watersheds with significant spatial heterogeneity thus
26 benefiting watershed research and decision supporting.

- We proposed a spatially hybrid-structure approach for hydrological modeling.
- Model structures are spatially varied and flexibly constructed in the approach.
- The approach is implemented based on extensions to SEIMS.
- The spatially hybrid model outperformed two conventional uniform models.

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46 **Keywords:** watershed simulation; hydrological modeling framework; hydrological
47 model structure; spatial heterogeneity; SEIMS

48 **1 Introduction**

49 Hydrological models provide an effective way to simulate and understand
50 complex hydrological processes in real-world watersheds. A variety of hydrological
51 models exist, with each suitable for different modeling requirements dictated by the
52 unique characteristics of a watershed and available data (Beven, 2000; Gharari et al.,
53 2021; Wagener et al., 2001). This suitability is fundamentally shaped by the model
54 structures they adopt. The structure of most hydrological models encompasses two
55 aspects: the spatial discretization, and the hydrological processes representation. The
56 spatial discretization involves simulating hydrological processes (e.g., evaporation,
57 infiltration, and channel routing) on specific spatial units (e.g., the entire watershed,
58 subbasin, channel lines, and grid cells). Meanwhile, the hydrological process
59 representations, which encapsulates the translation of real-world hydrological
60 processes into simulation algorithms, involves the selection of equations, numerical
61 solutions, and the temporal scale (e.g., annual, monthly, daily, and hourly) of
62 simulation. Therefore, the selection of an application-specific model structure stands
63 as the primary and critical step in hydrological modeling, as implied in many model
64 structure evaluation researches (Butts et al., 2004; David et al., 2022; Pilz et al., 2020;
65 van Esse et al., 2013).

66 The model structure determined for a watershed can be categorized into two
67 types, i.e., the uniform model structure, and the spatially varying model structure,
68 according to whether they are spatially varying within the watershed of interest. Most
69 research directly choose an existing model with a fixed or near-fixed model structure
70 which is uniform for the whole study area. Such a model as well as its model structure
71 are often developed with specific assumptions and intended for application in
72 constrained catchment characteristics. Examples of such single models include HBV
73 (Lindström et al., 1997), GR4J (Perrin et al., 2003), SWAT (Arnold et al., 1998),
74 TOPMODEL (Beven and Kirkby, 1979), RHESSys (Tague and Band, 2004), and
75 DHSVM (Wigmosta et al., 1994). Nevertheless, it is recognized that the uniform

76 model structure lacks flexibility in changing simulation units or customizing
77 alternative simulation algorithms of considered hydrological processes and thus
78 cannot accommodate watershed applications under diverse circumstances (Ley et al.,
79 2016; Savenije, 2009).

80 To accommodate complex application context with flexibility in controlling the
81 model structure compositions, researchers have increasingly turned to modular
82 hydrological modeling frameworks, such as ECHSE (Kneis, 2015), SUMMA (Clark
83 et al., 2015), MARRMoT (Knoben et al., 2019), SEIMS (Spatially Explicit Integrated
84 Modeling System; Liu et al., 2016; Zhu et al., 2019), and RAVEN (Craig, 2020).
85 These frameworks have been developed to integrate the compositions of multiple
86 existing models, allowing for easily customizing application-specific model
87 structures. It is typical that each of the interdependent modules within a hydrological
88 modeling framework simulates a specific part of the hydrological processes, and there
89 are often multiple alternative algorithms for simulating one hydrological process.
90 These modeling frameworks well support the concept of “multiple working
91 hypotheses”, as advocated by Clark et al. (2011). However, it is important to note that
92 these modeling frameworks primarily emphasize the application of a uniform model
93 structure across the entire application area, with spatial variability confined to input
94 data and model parameters. This way assumes that spatially heterogeneous data and
95 parameters are sufficient to capture the behavior of hydrologic processes, while the
96 model structure remains spatially uniform. While such a modeling way with spatially
97 uniform model structure yields satisfactory results in many applications, the uniform
98 model structure may be unreasonable and inaccurate to capture the characteristics of
99 the dominant hydrological processes when the application context (i.e., the watershed
100 characteristic or data availability) exhibit significant spatial heterogeneity.

101 Recognizing the limitation of the uniform-structure modeling approach, some
102 approaches have explored to construct spatially varying model structure within the
103 watershed under simulation. These approaches are mainly based on one of the two

104 different ideas: externally integrating individual models through unified model
105 interoperable interface, and internally integration within a hydrological modeling
106 framework. Examples of the external integration are the works of Liu et al. (2020), Li
107 et al. (2021), and Wang et al. (2021), as well as those works done through model
108 integration frameworks such as ESMF (Hill et al., 2004) and OpenMI (Harpham et
109 al., 2019). What they integrated are commonly individual models that simulates entire
110 hydrological processes, from rainfall to runoff. However, as a great deal of
111 interoperable interfaces often need to be implemented to integrate a model, the
112 flexibility of the external integration may be limited. The structures constructed in this
113 way are often fixed, and once the integrated model is established, it will require
114 further coding efforts to change the spatial constitution of the model structure, which
115 is difficult and inconvenient for most hydrologists.

116 To augment the modeling flexibility of spatially varying model structure, several
117 studies suggested the internal integration approach based on the modular hydrological
118 modeling frameworks. In this approach, model structures can be distributed to
119 different modeling areas in the watershed, with only minor change in configuration or
120 the main functions. This approach has been exemplified by works based on the
121 FLEX-Topo framework (Gao et al., 2014; Savenije, 2010), SUPERFLEX framework
122 (Fenicia et al., 2011, 2016), and airGR framework (Coron et al., 2017; Thébault et al.,
123 2023). Nevertheless, the hydrological modeling frameworks employed in these
124 studies are inherently limited to conceptual hydrological process representations, and
125 their spatial discretization is also confined to subbasins or hydrologic response units
126 (HRUs). Such a constraint on model structure poses a substantial challenge when
127 attempting to integrate and utilize distributed and physically-based models or
128 algorithms based on grid cells or patches.

129 As the state-of-the-art flexible approach to achieving spatially varying model
130 structure, existing internal integration studies based on modular hydrological
131 modeling framework only support lumped and conceptual model structures. This

132 inability of framework in supporting distributed and physically-based model
133 structures limits the flexibility and applicability during hydrological experimentation,
134 comparative analyses, and applications pertaining to diverse model structures. To
135 relieve such an inability, this paper proposes a novel spatially hybrid hydrological
136 modeling approach by enabling the spatial allocation of various simulation units and
137 simulation algorithms, comprising both conceptual and physically-based models, to
138 different areas within a watershed. The remainder of the paper is organized as follows:
139 Section 2 outlines the design of the proposed spatially hybrid modeling approach and
140 its implementation based on the SEIMS framework. Section 3 discusses the case
141 study, followed by presentation of results and discussion in Section 4, and conclusion
142 in Section 5.

143 **2 Method design and implementation**

144 **2.1 Basic idea**

145 The core design of the spatially hybrid modeling involves two aspects: the first is
146 the flexibility for model structure construction, which enables combination of
147 different spatial discretization methods and hydrological process representations
148 across the watershed of interest; the second is the ability to distribute individual
149 model structures to different areas within the watershed, and integrate them to be
150 executed under the same time loop.

151 The basic idea of designing the flexibly constructed model structure is to
152 decouple the hydrological process representations (or specifically, the simulation
153 algorithms) from being bound to particular spatial discretization methods
154 (specifically, the simulation units). For instance, the physically- and process-based
155 algorithms are typically applied to fine-scale simulation units such as grid cells for
156 both are assumed to describe the hydrological process in detail. Similarly, conceptual
157 algorithms are typically applied to lumped or coarse-scale units such as HRUs,
158 hillslopes, or subbasins.

159 Such a binding is not necessary, and conversely, the combination of these model
160 structure components have been acknowledged as effective. Hydrological modeling
161 can be approached through two main paradigms: the bottom-up way, based on
162 physical theories, and the top-down way, founded on empirical and conceptual
163 deductions. Each of these approaches has its own set of advantages and
164 disadvantages, depending on the circumstances (Clark et al., 2011; Hrachowitz and
165 Clark, 2017). The fusion and compromise between the two ways could often yield
166 advantages such as the ease of implementing, computational efficiency, and the data
167 requirements, as demonstrated by various studies (Gunduz and Aral, 2005; Liu et al.,
168 2020; Sidle, 2021) and popular models such as the SWAT and TOPMODEL.

169 The combination of distinct simulation units and algorithms is possible when the
170 simulation algorithms are categorized as computational independent or dependent,
171 according to whether the interaction among adjacent or upstream-downstream
172 simulation units is required or not. An essential constraint on the applicability of
173 simulation algorithms is that their computational dependencies must be satisfied by
174 the spatial relationship of simulation units provided by chosen spatial discretization
175 method. For example, the conceptual reservoir-based surface runoff generation
176 algorithm with the physically-based kinematic wave-based surface routing can be
177 integrated to be applied to grid cells, where computational dependency is satisfied by
178 the flow directions between grid cells; the physically-based Richards equation-based
179 surface runoff generation algorithm and the conceptual unit hydrograph-based surface
180 routing algorithm can be integrated to applied on HRUs, where no computational
181 dependency is required. Note that the computational dependency is only a basic
182 constraint, the rationality of the model structure is to be determined by the modeler's
183 knowledge and requirements. Thus, diverse model structures could be formed and
184 customized through combinations of compatible simulation units and simulation
185 algorithms under the same hydrological modeling framework (Fig. 1a and Fig. 1b).

186

187 Figure 1 Design of the proposed spatially hybrid modeling approach, which involves
188 a) incorporating diverse spatial discretization methods and hydrological process
189 representations and b) supporting their flexible combinations into model structure on
190 the MSAU level; c) enabling the spatial-varied allocation of these MSAU models.

191

192 Based on the flexible model structure construction, different areas within the
193 watershed should then be assigned distinct application-specific model structures and
194 executed after integration (Fig. 1c). In this study, the minimal unit for model structure
195 allocation is named as a model structure allocation unit (MSAU), which is currently
196 defined to be coincident with the subbasin unit. In other words, each subbasin adopts
197 a model structure and all subbasin-level model structures collectively constitute the
198 watershed model structure. These subbasin models are interconnected by the stream
199 network with upstream-downstream relationships. The execution sequence of
200 subbasin models can be determined accordingly. When the input requirements of all
201 downstream MSAUs are satisfied with the output of upstream MSAUs, the models
202 on each MSAUs can be integrated. Models on MSAUs without the upstream-
203 downstream relationship could be parallelly executed, otherwise sequentially.

204 **2.2 Design of the spatially hybrid hydrological modeling** 205 **approach based on the hydrological modeling framework**

206 **SEIMS**

207 Following the basic idea, the proposed spatially hybrid modeling approach is
208 designed based on the modular hydrological modeling framework SEIMS (Liu et al.,
209 2016; Zhu et al., 2019), for its flexible modular design and “subbasin-simulation unit”
210 two-level parallelization strategy. The detailed design of the proposed approach based
211 on SEIMS includes two aspects (Fig. 2): (1) Enabling the construction of model
212 structures with diverse simulation units and algorithms, which serves as the basis of
213 the flexibility and diversity of the watershed model constructed. This requires SEIMS

214 to be extended on the spatial discretization methods and upgrading the simulation
215 modules to accommodate to different simulation units. (2) Enabling the spatial-varied
216 allocation of individual model structures and their integrated execution.

217

218 Figure 2. Overall design of the spatially hybrid hydrological modeling approach
219 based on extension to the Spatially Explicit Integrated Modeling System (SEIMS),
220 which includes a) supporting various spatial discretization methods; b) supporting
221 flexible application of the simulation unit to compatible simulation units; and c)
222 supporting spatial-varied model structure allocation.

223

224 **2.2.1 Brief introduction to the modular design and parallelization strategy of** 225 **Spatially Explicit Integrated Modeling System (SEIMS)**

226 SEIMS provides standard and concise interfaces to implement the simulation
227 algorithms into modules, which involves hillslope process simulation modules on grid
228 cells and channel routing process simulation modules on channel segments or channel
229 grid cells. Each module exposes input and output information via metadata for the
230 integration with other modules. Therefore, a list of user-configured modules
231 comprises a SEIMS-based model in a loosely coupled manner. To support the flexible
232 model structure configuration required in the proposed approach, the spatial
233 discretization methods as well as the module library of SEIMS should be expanded
234 (Fig.2a and 2b; detailed in Section 2.2.2).

235 The two-level parallelization strategy of SEIMS treated subbasin as relative
236 independent spatial units for hydrological modeling dispatched to dedicated
237 computing processes through the Message Passing Interface (MPI). The simulation
238 tasks on grid cells within a subbasin are dispatched among computing threads via the
239 Open Multi-Processing (OpenMP). Although the parallelization strategy underpins the
240 relative independence of computations within each subbasin, thereby providing the

241 potential to apply different model structures to distinct subbasins, the simulation
242 modules and simulation units are predefined to be uniform for the whole watershed.
243 These modules are loaded based on a configuration text file that sequentially records
244 the modules involved. Therefore, the execution of SEIMS-based model should be
245 upgraded to allocate different model structures to subbasins and executed
246 independently (Fig. 2c; detailed in Section 2.2.3).

247 **2.2.2 Constructing model structures with diverse simulation units and algorithms** 248 **based on extension to SEIMS**

249 To enable the flexible customization for a hybrid structure, the diversity of both
250 spatial discretization methods and hydrological process representations should be
251 guaranteed. For spatial discretization, the hydrological response unit (HRU) could be
252 added as a simulation unit type in SEIMS, thus enabling the simulation based on not
253 only grid cells but also HRUs. The HRUs, generated using soil and land-use maps,
254 could follow the parameterization methodology of semi-distributed models and
255 support both conceptual and physically-based parameters. Physically-based
256 parameters can be derived from the actual properties of the soil or land-use data,
257 while conceptual parameters are directly specified within the soil and land-use lookup
258 tables. For instance, the reservoir capacity within an HRU can be represented by the
259 soil depth associated with that specific HRU area.

260 Under such a HRU discretization method, the hillslope and subbasin simulation
261 unit can be supported with SEIMS, as specialized cases of HRUs. For example,
262 subbasin simulation is achieved when all HRUs within a subbasin share identical
263 parameter values. With the above extension for spatial discretization method, SEIMS
264 will offer the flexibility of utilizing subbasin, hillslopes, HRUs, and grid cells as
265 spatial discretization options, allowing modelers to choose the most appropriate
266 option for specific modeling needs.

267 The expansion of diverse discretization methods within SEIMS necessitates a

268 corresponding extension of the hydrological process library to support the flexible
269 combination of conceptual and physically-based processes across different
270 discretization methods. SEIMS was designed to integrate algorithms simulating one
271 specific processes, while it previously lacked a conceptual model capable of
272 considering multiple hydrological processes comprehensively. To bridge this gap, the
273 lumped conceptual models could be integrated as separate process-based modules:
274 surface runoff modules that generate runoff at each simulation unit, and surface
275 routing that directly convey water to the subbasin outlet. Such modules could be
276 applied to any simulation unit in SEIMS, including grid cells, HRUs, hillslopes, and
277 subbasins. Following this schema, a representative of widely used conceptual models,
278 GR4J (Perrin et al., 2003), was incorporated into the SEIMS module library.

279 To ensure the compatibility of module combinations with the spatial
280 discretization method applied to subbasins, the module interface of SEIMS is
281 extended to mark its computational dependency requirement as one of the following
282 two types.

- 283 - computational dependent: exclusively applicable to grid cells, where water is
284 routed based on flow directions derived from digital terrain analysis. A model
285 structure containing any computational dependent module can only be
286 applied to the MSAU with the simulation unit of grid cell.
- 287 - computational independent: applicable to any simulation unit, including grid
288 cells, HRUs, subbasins, and the entire watershed within SEIMS.

289

290 **2.2.3 Allocating individual model structures to MSAUs based on SEIMS**

291 An essential aspect of implementing the spatially hybrid hydrological modeling
292 method is to enable the allocation of individual model structures to different MSAUs
293 within the watershed. This entails allowing the separate construction and execution of
294 individual models on each MSAU, referred to as MSAU models (or subbasin models

295 in this study), which are subsequently integrated into a watershed model. This
296 requires the MSAUs to be treated individually in an objective-oriented manner. To
297 achieve flexible and swift model construction and modification, the structure
298 configuration should be text-based rather than hard-coded.

299 Among the above-mentioned requirements, the subbasin-separate simulation and
300 flexible model configuration are compatible to the two-level parallelization strategy
301 and text-based module configuration of SEIMS, as illustrated in section 2.2.1. While
302 extension should still be implemented on its module configuration method to support
303 spatial-varying model structure allocation. To facilitate such an ability, the
304 configuration files should be extended to include the subbasin number it is assigned
305 to, and the discretization method the subbasin adopts, given that the MSAU is defined
306 to be subbasins in this study. This allows an individual configuration when the
307 computing processes of each subbasin dynamically read the configuration files, load
308 each module, and retrieve the spatial parameters of each subbasin with the specified
309 discretization method.

310 Extension should also be made on the design of the two-level parallel computing
311 strategy to enable the execution of the individual subbasin models in SEIMS. In the
312 original strategy, the simulation unit within a subbasin particularly refers to the grid
313 cells, while simulation at the HRU level was not fully considered and implemented.
314 To extend this strategy, the HRUs could be designed in a manner similar to grid cells
315 but without topological orders, and are directly distributed to different computing
316 threads using OpenMP. the subbasin-level parallelization could remain unchanged,
317 with subbasins hierarchically sorted based on their flow relationships and
318 subsequently assigned to different computing processes using MPI.

319 This enhanced strategy allows subbasin models to operate within the same time
320 loop, enabling the parallel execution of hillslope processes among subbasins, with the
321 output at each subbasin's outlet exchanged with its downstream subbasin using the
322 configured channel routing module. The routing modules of SEIMS are retained and

323 not extended to allow for spatial variation, as the hillslope processes with spatial
324 variability are considered sufficient to represent the heterogeneity of hydrological
325 processes.

326 **2.3 Current implementation**

327 The implementation of the proposed approach with SEIMS involves
328 modifications to both the preprocessing and the main modeling programs of SEIMS.
329 In the original Python-based preprocessing program, spatial parameters of a
330 watershed, including terrain, land-use, soil, and meteorological data, are distributed to
331 grid cells organized by subbasins. The new implementation introduces support for
332 HRU-based delineations, such as subbasins and hillslopes. This entails calculations of
333 spatial parameters for multiple times for every subbasin and every type of simulation
334 unit specified in the configuration file. The main modeling program and the module
335 library of the SEIMS are based on the C++ language. They have been extended to
336 distinguish and retrieve the spatial parameters, which are stored in MongoDB,
337 corresponding to the simulation unit type of subbasin. The declaration of
338 computational dependency is also added to every module in the module library.

339 With the SEIMS extensions introduced in this study, users can now construct
340 diverse model structures by selecting alternative simulation modules, and assign these
341 structures to any subbasin within a watershed all through text-based configuration
342 editing. The SEIMS is open-source on GitHub (<https://github.com/lreis2415/SEIMS>)
343 and under continuous development.

344 **3 Case study**

345 **3.1 Study area and data**

346 In this study, we selected the Babao River watershed at Qilian, Qinghai Province,
347 China, in the upper reaches of the Heihe River Basin as the case study area to verify
348 the proposed approach through daily-scale runoff simulation. The Babao River

349 watershed Figure 3 is one of the headwaters of the Heihe River Basin. It is located in
350 a high-altitude, cold and mountainous region with an area of approximately 2511 km².
351 The average elevation is 3565 m, and the region features glacier, snow cover and
352 frozen soil.

353 This study extensively relies on publicly available data. We used the 3"
354 resolution (approximately 90 m) MERIT DEM sourced from Yamazaki et al. (2017)
355 for watershed delineation and calculation of terrain attributes. Meteorological input
356 data for the model were obtained from the China Meteorological Assimilation Driving
357 Datasets for the SWAT model (CMADS) version 1.2, provided in the form of
358 approximately 0.125 ° resolution gridded station data (Meng et al., 2019). Land cover
359 data for the model were derived from GLOBELAND30 with a resolution of 30 m
360 (<http://www.globallandcover.com>). Soil attribute input data for the model were
361 sourced from the Harmonized World Soil Database (HWSD; Wieder, 2014).

362

363 Figure 3. The Babao River watershed in the upper reaches of the Heihe River Basin
364 and the spatial constitution of the spatially hybrid model.

365

366 **3.2 Experimental setting**

367 Two individual model structures were adopted to construct the spatially hybrid
368 model. One is a physically-based model structure using grid cells as the simulation
369 unit, providing a more detailed representation of spatial and hydrological processes.
370 This structure holds promise for simulating regions with significant elevation
371 variations, such as mountainous areas within the watershed. The other was a
372 conceptual model structure with HRUs as the simulation units, which offers simplicity
373 and can generalize multiple hydrological processes. The HRU are derived from the
374 land-use and soil maps. This structure was assumed to be well-suited for large, gently

375 sloping terrain within the watershed, compared to the physically-based structure. The
376 algorithms for hydrological process description of the two model structures are listed
377 in Table 1. Note that the physically-based structure includes both physically-based
378 modules (such as the interflow module that calculates the flow cell by cell) and
379 conceptual modules (such as the surface routing module based on unit hydrograph),
380 which reflects the flexibility of the supported model structures.

381

382 Table 1. The modules adopted for the physically-based model and the conceptual
383 model.

384

385 However, since the lack of modules for permafrost and glaciers in SEIMS, a
386 purely physically-based model, if applied, may be confronted with inaccuracies in
387 representing certain processes. Therefore, a spatially hybrid model structure
388 combining both physically-based and conceptual models can be considered in this
389 watershed to achieve more accurate runoff simulations. Under this assumption, a
390 combination of conceptual and physically-based model structures was allocated to
391 different subbasins in the Babao River watershed, resulting in a spatially hybrid
392 model, as depicted in Figure 3. Another two model structures were established for
393 comparison. The first model exclusively utilized the physically-based model for all
394 subbasins, referred to as the physically-based model. The second model employed the
395 conceptual model structure for all subbasins, referred to as the conceptual model.

396 The three model structures described above were utilized in a four-year
397 simulation, spanning from January 1, 2013, to December 30, 2016. The first year
398 (2013) served as a warm-up period, followed by two years (2014 and 2015)
399 designated for calibration, and the final year (2016) for validation. Various
400 performance indices, including the Nash-Sutcliffe coefficient (NSE), root mean
401 square error-standard deviation ratio (RSR), percent bias (PBIAS), and R-square,
402 were selected to evaluate the modeling performance. Parameter calibration was

403 conducted using the NSGA-II genetic algorithm integrated in the SEIMS framework,
404 with a population size of 200 and optimization for 15 generations. The calibration
405 objectives are maximum NSE, minimum absolute values of RSR and PBIAS. The P-
406 factor and R-factor were used as additional indicators on the prediction uncertainty,
407 where P-factor is the percentage of observations fall within the 95% prediction
408 uncertainty (PPU) interval, and R-factor is the average width of the 95% PPU
409 interval, normalized by the standard deviation of the observed data. The two factors
410 are utilized to evaluate the final generations of the experimental model structures.
411 Comparative analysis was carried out to assess the simulation performance of the
412 three model sets based on the optimal parameters obtained during calibration.

413 **4 Results and discussion**

414 **4.1 Quantitative performance of the spatially hybrid model**

415 **structure constructed by the proposed approach**

416 Figure 4 illustrates the calibration results of the three model structures, revealing
417 that the spatially hybrid model (Figure 4c), established using the proposed approach,
418 outperforms the others in terms of the best-fit simulations. The NSE of the best-fit
419 spatially hybrid model is the highest (0.63 / 0.81 for calibration / validation period,
420 the same below), compared to the physically-based model (0.34 / 0.73) and
421 conceptual model (0.45 / 0.61). The lowest RSR (0.61 / 0.43), lowest PBIAS (3.66% /
422 -4.62%) and highest R-square (0.64 / 0.83) are also seen in the spatially hybrid model,
423 which indicates a best fit among the experimental model structures.

424

425 Figure 4. The simulation results of the final generation in calibration of the (a)
426 physically-based model, (b) conceptual model, and (c) the spatially hybrid model
427 from the proposed approach.

428

429 In terms of P-factor and R-factor, the spatially hybrid model shows a medium P-

430 factor (0.42 / 0.30) and the lowest R-factor (0.60 / 0.49). In comparison, the
431 physically-based models show the lowest P-factor (0.26 / 0.37) with a medium R-
432 factor (0.65 / 0.57), which indicates a lower prediction uncertainty among the
433 population compared to the conceptual models, while the accuracy is also low. The
434 conceptual models, while having the highest P-factor (0.57 / 0.51), show a wide
435 prediction interval with the highest R-factor (1.36 / 1.03). This indicates that although
436 the observed discharge values are more within the prediction interval of conceptual
437 models, the uncertainty is also high. The result shows the spatially hybrid model
438 structure has a more concentrated prediction with the lowest uncertainty in the last
439 generation during optimization. While uncertainty may originate from multiple
440 sources including parameters and model structure, this result also implies a potential
441 advantage in achieving more possibly accurate results through parameter
442 optimization.

443 **4.2 Discussion on the simulation results in terms of the** 444 **hydrographs from the proposed approach**

445 The strength of the spatially hybrid model becomes more evident when
446 examining the visual interpretation of the simulation results (Figure 5). To elucidate
447 this, we begin by discussing the disparities between the physically-based model and
448 the conceptual model (Figure 4a and 4b). In dry seasons, typically from November to
449 the following April when baseflow is the primary contributor to discharge, the
450 physically-based model exhibits a noticeable underestimation of baseflow during the
451 dry season between 2015 and 2016. This discrepancy suggests potential inaccuracies
452 in representing groundwater processes. Conversely, the conceptual model provides an
453 overall reasonable simulation but at the cost of overestimating baseflow. This
454 overestimation can serve as compensation for low flows in wet seasons, which
455 typically occur from May to October. In the wet seasons, the physically-based model
456 produces steeper rising and falling limbs in the hydrographs, corresponding to the

457 intensive precipitation during wet seasons, as depicted in Figure 5. This behavior
458 aligns with its physical basis. The conceptual model, on the other hand, struggles to
459 simulate the peak flows accurately, especially during the validation period.

460

461 Figure 5. Hydrograph of the best-fit spatially hybrid model.

462

463 The spatially hybrid model, as a result, combines the strengths of both models.
464 While it tends to slightly overestimate baseflow, it outperforms both the physically-
465 based model (which underestimates) and the conceptual model (which overestimates)
466 and provides more precise and steeper peak flows during the wet season. This
467 represents an enhancement to the advantages of the physically-based model. In areas
468 with gentle terrain, groundwater tends to accumulate. However, during the period
469 from October 2015 to May 2016, when overall precipitation was low, the physically-
470 based model's process-based simulations may have resulted in an underestimation of
471 groundwater levels. In contrast, the conceptual model, through adjustments to
472 parameters governing groundwater outflow, can reconcile these levels with observed
473 values. In the mountainous regions within the watershed, characterized by rapid
474 runoff generation and routing, the conceptual model may not accurately capture these
475 dynamics, resulting in less precise simulations of rainfall-induced runoff. However,
476 this limitation is offset within the hybrid model due to the inclusion of the physically-
477 based model.

478 An additional merit of the spatially hybrid model lies in the computational
479 efficiency. Due to the detailed representation of various hydrological processes in the
480 physically-based model, its calibration took approximately 100 hours for 3000 model
481 runs (200 population and 15 generations). Such a high calibration demand limits its
482 availability to larger watersheds. In contrast, the calibration time for the conceptual
483 model was significantly shorter, approximately 15 minutes. Therefore, the spatially
484 hybrid model, which contains both models, exhibited an intermediate calibration time

485 of around 50 hours, proportionate to the participation of the two models. This
486 efficiency enhancement suggests a broader applicability to larger watersheds, where
487 specific subbasins of interest can be treated individually. This approach not only saves
488 time but also enables the production of more model runs for parameter optimizations
489 or uncertainty analysis.

490 **5 Conclusion**

491 This paper introduces a novel spatially hybrid hydrological modeling approach,
492 offering a versatile solution to address the challenges posed by the spatial
493 heterogeneity of complex watersheds. Unlike traditional distributed hydrological
494 models that allow only spatial variability of parameters, the proposed approach takes
495 a divide-and-conquer idea to accommodate spatially varied and hybrid model
496 structures. It introduces the concept of Model Structure Allocation Units (MSAUs) for
497 allocating individual model structures. This approach advocates the hybrid
498 combination of different spatial discretization methods and hydrological process
499 representations, enhancing structural flexibility on each MSAU. Constraints on the
500 MSAU model structures are discussed to ensure their integration into the final
501 watershed model.

502 Based on the implementation on the hydrological modeling framework SEIMS,
503 an experiment was conducted to validate the effectiveness of the proposed approach.
504 The spatially hybrid model structure, compared to uniform physically-based and
505 conceptual model structures, demonstrated not only the capability of modeling with
506 spatially varied and flexible structure, but also the ability to synergize the strengths of
507 the constituent model structures, potentially leading to reduced uncertainty.

508 This approach empowers researchers to scrutinize and fine-tune model structures
509 with precision, aligning them with the unique characteristics of specific areas within a
510 watershed. It offers enhanced flexibility and a wider range of available model
511 structures, extending the horizons of hydrological modeling for spatially varying

512 model structures. This extension facilitates the exploration of multiple working
513 hypotheses, ultimately enhancing our understanding of complex watershed systems.

514 However, there are also limitations in the current implementation. First, while
515 the concept of MSAUs (model structure allocation units) is theoretically applicable to
516 other simulation units, such as HRUs or coarse grid cells, further exploration is
517 needed to assess its suitability on these units. Second, the SEIMS module library must
518 undergo further development to encompass a broader spectrum of models and
519 algorithms, particularly those related to glacier and frozen soil processes, in order to
520 construct model structures for a wider range of applications in watersheds with
521 significant spatial heterogeneity. Lastly, as the spatial constitution of the spatially
522 hybrid model can be freely configured and revised, determining the optimal spatial
523 constitution remains a subject for future study.

524

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533

534

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Figure 1. Design of the proposed spatially hybrid modeling approach, which involves a) incorporating diverse spatial discretization methods and hydrological process representations and b) supporting their flexible combinations into model structure on the MSAU level; c) enabling the spatial-varied allocation of these MSAU models.

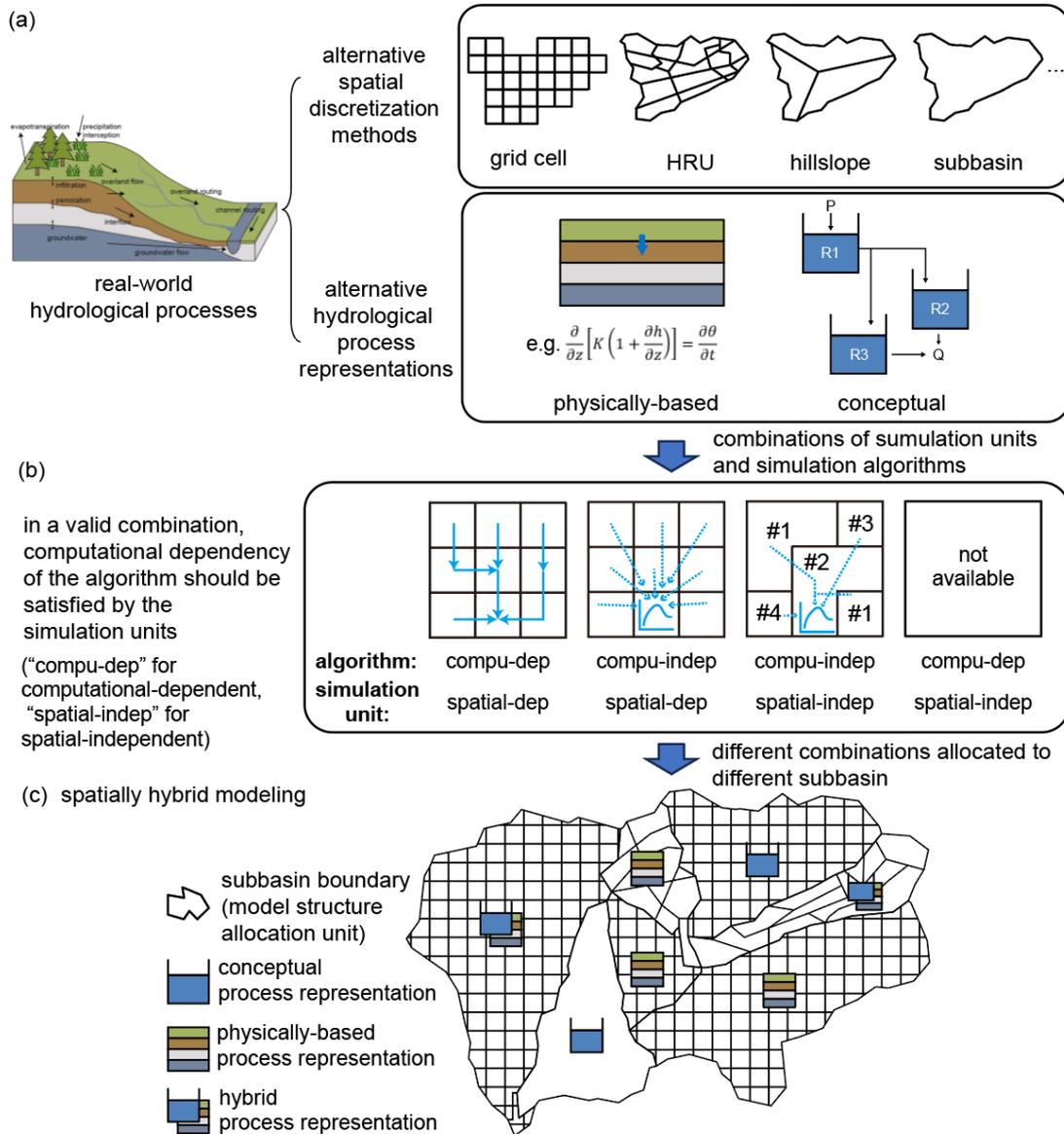


Figure 2. Overall design of the spatially hybrid hydrological modeling approach based on extension to the Spatially Explicit Integrated Modeling System (SEIMS), which includes a) supporting various spatial discretization methods; b) supporting flexible application of the simulation unit to compatible simulation units; and c) supporting spatial-varied model structure allocation.

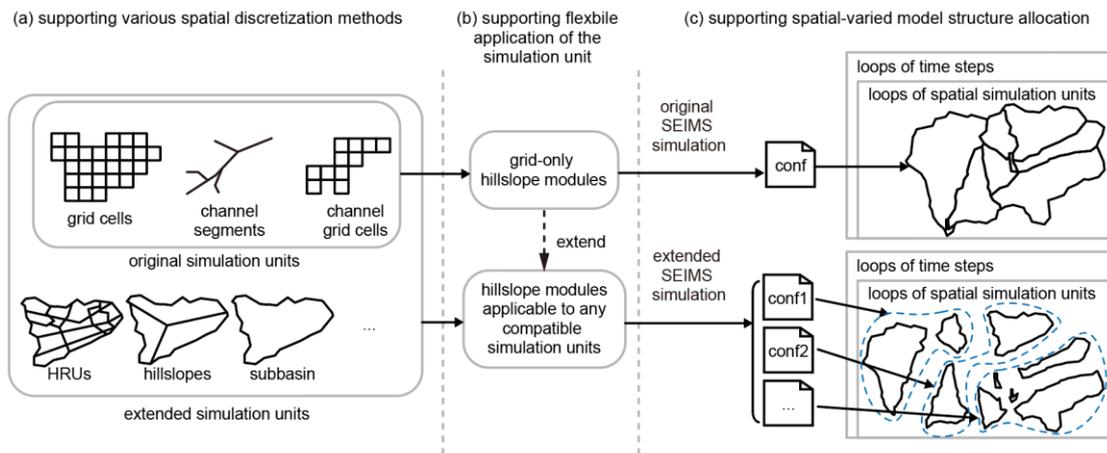


Figure 3. The Babao River watershed in the upper reaches of the Heihe River Basin and the spatial constitution of the spatially hybrid model.

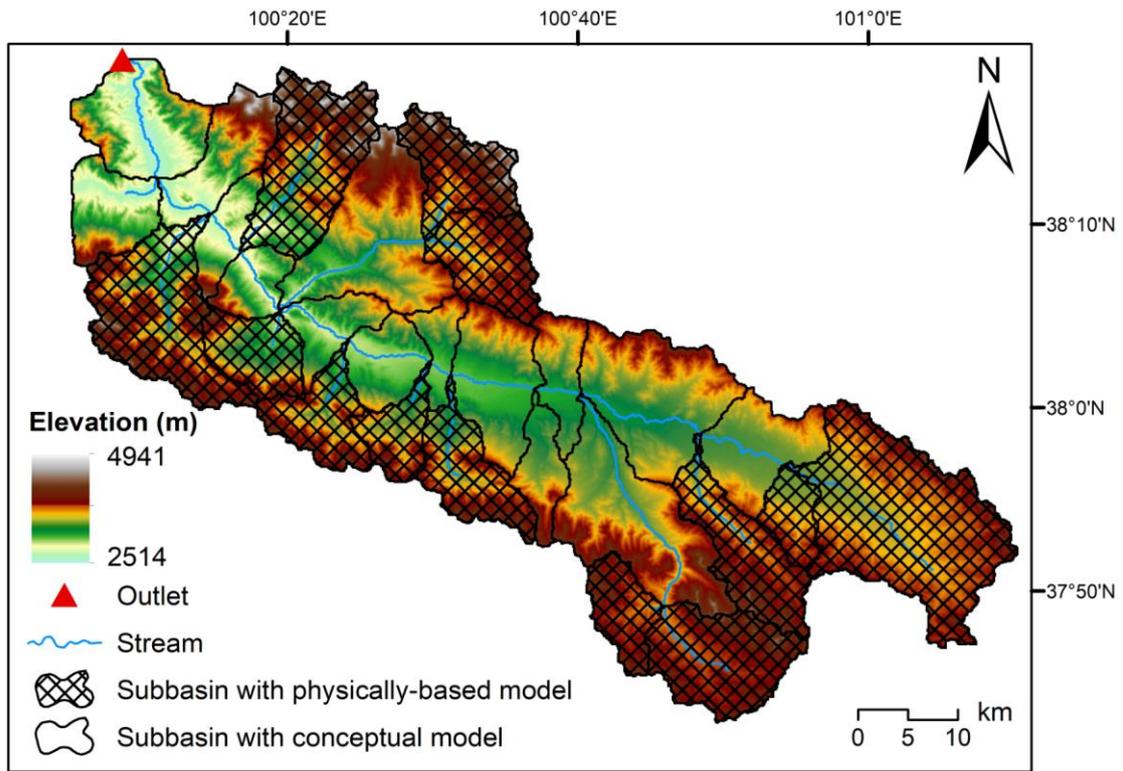


Figure 4. The simulation results of the final generation in calibration of the (a) physically-based model, (b) conceptual model, and (c) the spatially hybrid model from the proposed approach.

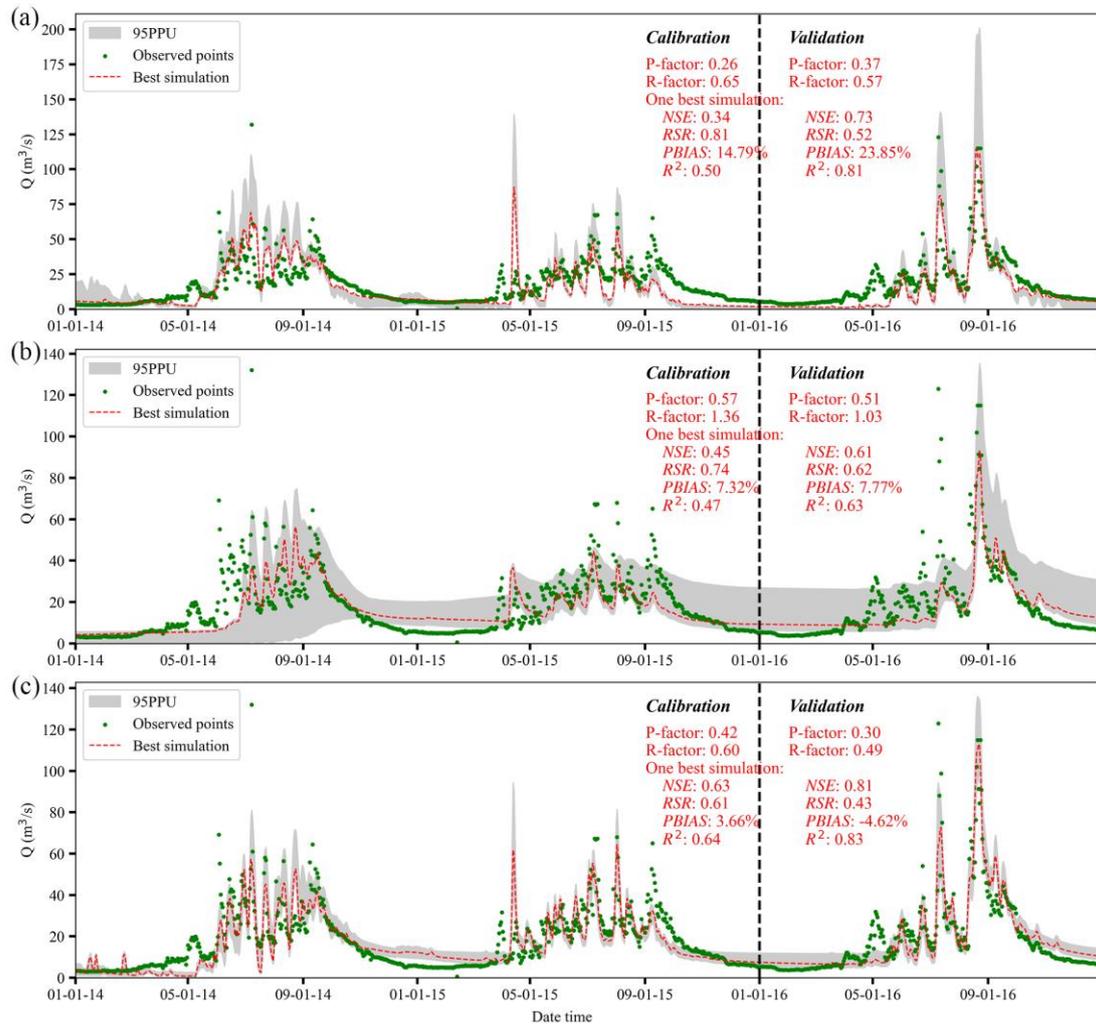


Figure 5. Hydrograph of the best-fit spatially hybrid model.

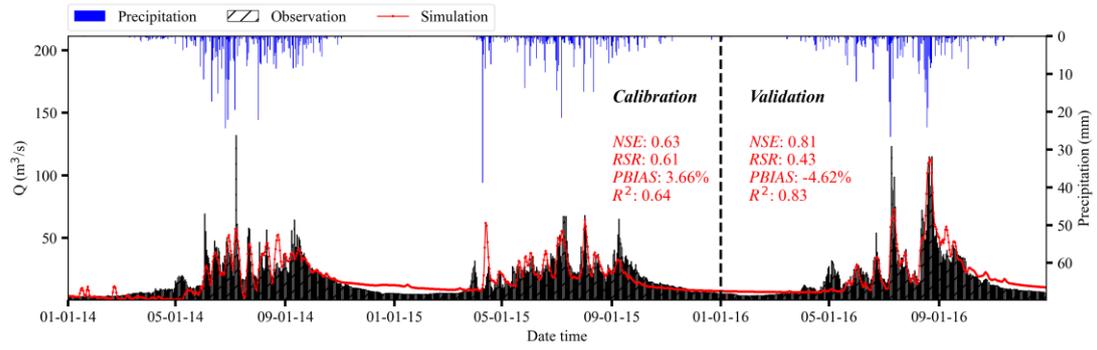


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Figure 5. Hydrograph of the best-fit spatially hybrid model.

Table 1. The modules adopted for the physically-based model and the conceptual model.

Hydrological processes	Modules of the physically-based model	Modules of the conceptual model
Conceptual and comprehensive surface runoff	(NA)	GR4J
Potential evapotranspiration	Penman Monteith	Hargreaves
Interception	Maximum canopy storage	(NA)
Snow melt	Snowpack Daily	
Infiltration and surface runoff	Modified rational	
Depression	Linsley	
Percolation	Storage routing	
Interflow	One-dimension kinematic wave	
Actual evaporation	Hargreaves and Priestley Taylor	
Plant growth	Simplified EPIC	
Groundwater	Linear reservoir	
Surface routing	Geomorphology-based unit hydrograph	
Channel routing	Muskingum	Muskingum