A spatially hybrid hydrological modeling approach using subbasin-specific model structures

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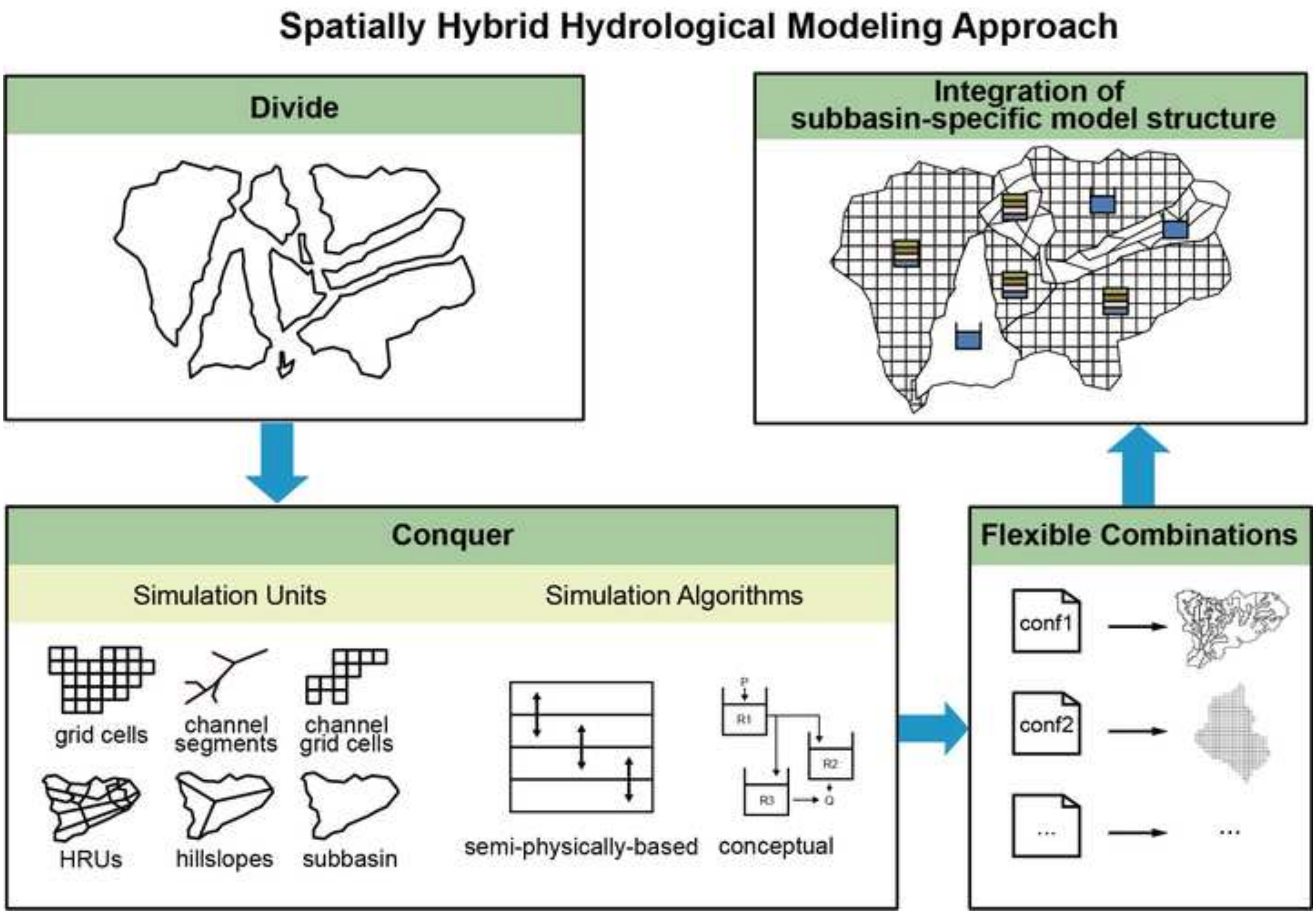
Highlights

- An approach to supporting spatially hybrid hydrological model structures is proposed.
- Diverse subbasin-specific model structures are integrated for watershed-scale simulation.
- Model structure flexibly combines compatible spatial units and simulation algorithms.
- Spatial units of subbasin, hillslope, HRU, and cells support conceptual or semi-physical algorithms.
- Spatially hybrid model from the proposed approach improves general performance.


Spatially Hybrid Hydrological Modeling Approach
Divide
Integration of subbasin-specific model structure
Conquer
Simulation Units
Simulation Algorithms
grid cells
channel segments
channel grid cells
HRUs
hillslopes
subbasin
semi-physically-based
conceptual
Flexible Combinations
conf1
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Abstract:

Hydrological models that typically adopt spatially consistent model structures are often unfit for complex application contexts with significant spatial heterogeneity. Although existing hydrological modeling frameworks support spatially varying lumped or semi-distributed conceptual model structures, they face a significant challenge in integrating distributed physically-based model structures. This paper proposes a new spatially hybrid hydrological modeling approach, which flexibly combines compatible spatial units and simulation algorithms to construct different model structures for individual subbasins within interest watershed, and then coherently integrate them through channel routing to perform watershed-scale simulation. Implemented within the Spatially Explicit Integrated Modeling System, this approach was evaluated in a medium-sized watershed with two distinct model structures: a lumped conceptual model structure for gently sloping subbasins and a fully-distributed semi-physically-based model structure for mountainous subbasins. Comparative experiments demonstrated that the hybrid model combines the strengths of both, improving general performance. The proposed approach enhances modeling flexibility towards knowledge-driven intelligent modeling in spatially heterogeneous environments.

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

Software availability statement

Software: SEIMS (Spatially Explicit Integrated Modeling System)

Developers: Yu-Jing Wang, Liang-Jun Zhu

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Operating systems supported: Windows, Linux, and macOS

Language: C++ and Python

Source code: The archived version supporting this paper can be accessed vis the OSF site at https://doi.org/10.17605/OSF.IO/D5WUR. For the continuous development version, please visit the GitHub repository at https://github.com/lreis2415/SEIMS.

Documentation: Documentation for running the proposed approach is available at https://osf.io/vwxkr, with the continuous user manual for the SEIMS framework accessible at https://lreis2415.github.io/SEIMS/.

1 Introduction

Hydrological models serve as effective tools for simulating and enhancing our understanding of complex hydrological processes in real-world watersheds. A variety of hydrological models have been developed, each suited to different application contexts depending on multiple factors such as watershed characteristics and available data (Beven, 2000; Gharari et al., 2021; Wagener et al., 2001). Building an application-specific model that is both hydrologically reasonable and practically executable stands as the primary and critical step for hydrological modeling and applications such as scenario analysis of watershed management (Butts et al., 2004; David et al., 2022; Pilz et al., 2020; Qin et al., 2025; van Esse et al., 2013).

The model structure of a hydrological model can be defined by its spatial discretization scheme and the representation of hydrological processes (Chow, 1988; Milad et al., 2012; Hrachowitz and Clark, 2017). The spatial discretization scheme refers to the arrangement of one or more types of spatial units (also known as simulation units) within the watershed for hydrological simulation (Dehotin and Braud, 2008). Lumped spatial units typically ignore or broadly generalize the spatial heterogeneity of watershed characteristics, including either coarse-scale units (such as a subbasin or even an entire watershed), or units defined by dominant combinations of selected geographic attributes (Arnold et al., 2010). In contrast, semi- or fully-distributed spatial units can fully cover the entire geographic spatial domain of the watershed at varying levels of details, such as spatially explicit HRUs (hydrological response units; Teshager et al., 2016) and grid cells (Wigmosta et al., 1994). The representation of hydrological processes denotes the simulation algorithms used for hydrological phenomena (e.g., infiltration and surface flow routing). Conceptual representations simplify hydrological processes with a few lumped components, typically using conceptual reservoirs (or buckets) (Fenicia et al., 2011; Knoben et al., 2019). In contrast, fully-physically-based representations apply fundamental physical laws (e.g., mass, momentum, and energy conservation) by solving coupled partial differential equations (Abbott et al., 1986; Shu et al., 2020). To balance physical realism with computational feasibility, semi-physically-based representations employ simplified physical equations for individual hydrological processes that are generally simulated independently (Arnold et al., 1998; Tague and Band, 2004; Tang et al., 2019).

Existing methods of determining model structures can be categorized as spatially consistent method and spatially varying method. The spatially consistent model structure means the types of simulation units and simulation algorithms for interested hydrological processes are the same for the whole watershed. Most research on directly choosing a single existing hydrological model with a fixed model structure falls into this category. A more flexible choice is utilizing modular hydrological modeling frameworks, which emphasize various aspects of flexibility in customizing application-specific model structures, such as extensible types of simulation units and associated simulation algorithms (Kneis, 2015), and alternative simulation algorithms for individual hydrological processes (Clark et al., 2015; Craig, 2020; Knoben et al., 2019; Zhu et al., 2019). However, their default design or most common application remains on customizing and applying a spatially consistent model structure. This method inherently assumes that the spatial variability of watershed characteristics can be adequately captured by the required input data and parameters. However, using a fixed model structure may fail to effectively accommodate diverse and complex application contexts exhibiting significant spatial heterogeneity (Ley et al., 2016; Savenije, 2009; Sui and Turner, 2021).

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

To further enhance the flexibility of spatially varying model structures, another idea involves internally constructing and integrating multiple model structures within a single modular hydrological modeling framework such as FLEX-Topo (Topography-driven Flux Exchange hydrological model; Gao et al., 2014; Savenije, 2010), SUPERFLEX (SUPER Flux Exchange hydrological model; Fenicia et al., 2011, 2016), and airGR (Suite of GR Hydrological Models; Coron et al., 2017; Thébault et al., 2024). These frameworks allow the assignment of different model structures to different modeling areas within the watershed with only minimal changes to configuration or source code (Thébault et al., 2024). Nevertheless, these frameworks are fundamentally limited to conceptual representations of hydrological processes, with simulation units typically being subbasins and HRUs. Therefore, these state-of-the-art flexible frameworks primarily support lumped or semi-distributed conceptual model structures and thus face a significant challenge in integrating physically-based simulation algorithms and spatially explicit distributed simulation units.

To address this limitation, we propose a new and practically significant spatially hybrid modeling approach. This approach enables the flexible combination of compatible spatial units and simulation algorithms to construct distinct model structures for individual subbasin within the watershed, such as lumped conceptual and fully-distributed semi-physically-based model structures. Subbasin-level model structures are coherently integrated through channel routing to perform watershed-scale simulation. The remainder of this paper is organized as follows: Section 2 outlines the design of the proposed approach and its implementation within the

SEIMS (Spatially Explicit Integrated Modeling System; Zhu et al., 2019) framework, Section 3 presents an experimental 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 employing a divide-and-conquer strategy to construct and execute different model structures for relatively independent areas within the watershed. A watershed can be divided into distinct closed catchment areas connected by the channel network, i.e., subbasins. Thus, subbasins are naturally suited to serve as the divide-and-conquer modeling units, each configurable with an individual model structure. Therefore, the core design of this approach involves two key aspects: 1) flexibility in constructing model structures, and 2) the capability to integrate these subbasin-specific model structures to perform watershed-scale simulation.

The idea in designing a flexible model structure is to ensure compatibility between the spatial discretization scheme (i.e., simulation units) and hydrological process representations (i.e., simulation algorithms). Both can be classified according to their dependencies, which determine their compatibility (Figure 1a). For simulation units, dependency (or connectivity) refers to whether spatially explicit relationships exist between units. For simulation algorithms, computational dependency refers to whether a simulation on one unit relies on outputs (e.g., water flows or state variables) from adjacent or upstream units (Figure 1b). Therefore, a valid combination requires that computational dependencies of selected simulation algorithms are satisfied by the spatial connectivity of the simulation units (Figure 1b). For instance, a conceptual reservoir-based surface runoff generation algorithm combined with a physically-based kinematic wave-based surface routing can be applied to grid cells, where computational dependency is satisfied by the flow directions between grid cells. Another example is the combination of a physically-based Green-Ampt surface runoff generation algorithm with a conceptual unit hydrograph-based surface routing algorithm for application on HRUs (Craig, 2020), which requires no computational dependency. It is crucial to note that while computational dependency is a fundamental constraint, the ultimate rationality of a customized model structure relies on the modeler's hydrological knowledge and application-specific requirements.

Each subbasin model simulates hillslope processes and the channel routing process. In this study, it is assumed that mass and energy are exchanged between subbasins only through the channel network. Thus, the channel routing components within each subbasin model structure (e.g., the Muskingum method) are used to couple with their upstream and downstream subbasins, integrating all subbasin model structures into a comprehensive watershed model (Figure 1c). The channel routing of a downstream subbasin relies on outputs from its upstream channels. This dependency implies that the hillslope processes of each subbasins can be parallelized to improve computing efficiency, while channel routing processes of each subbasins must be executed sequentially according to the upstream–downstream network structure (Liu et al., 2016).

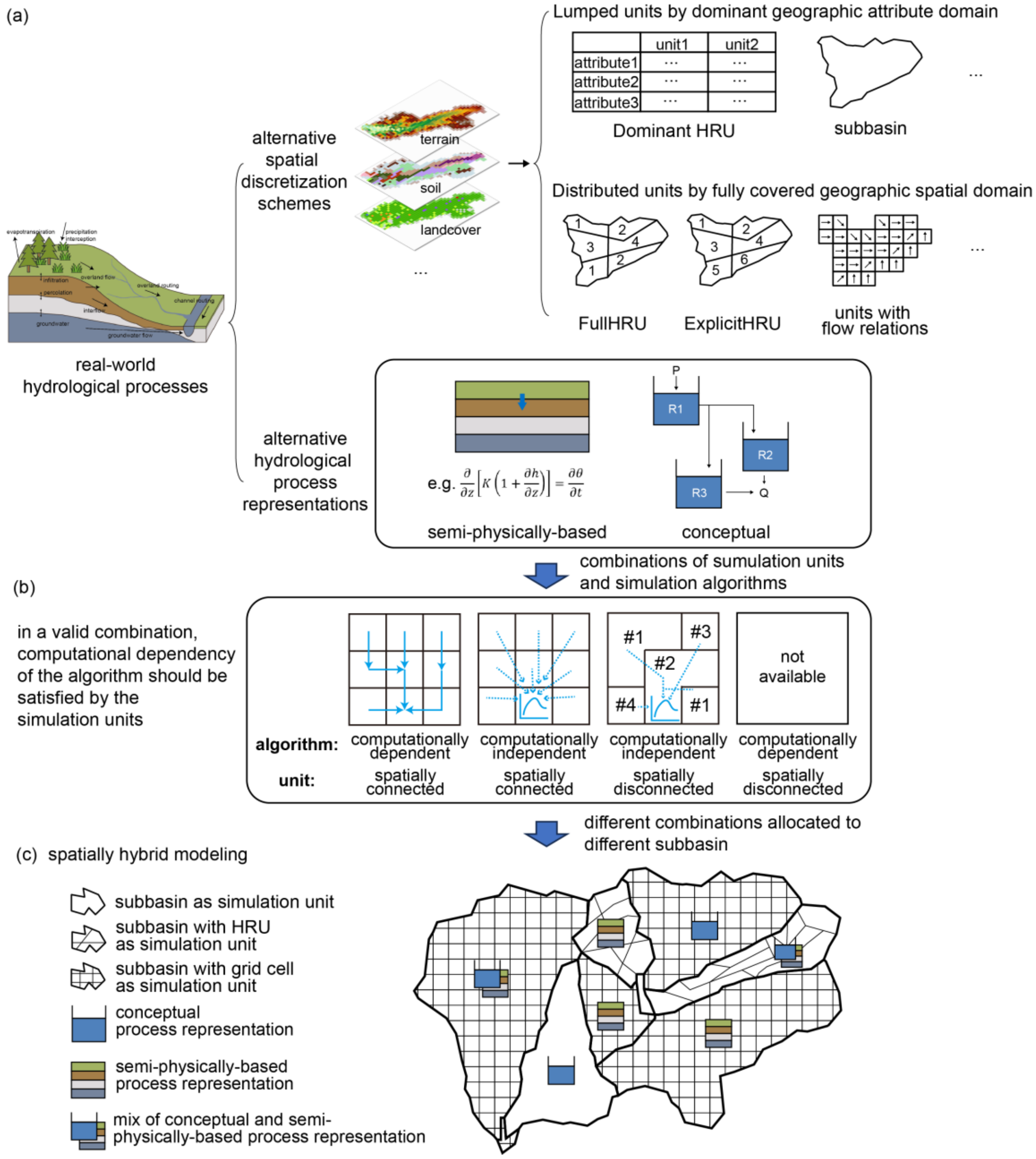

Figure 1. Design of the proposed spatially hybrid hydrological modeling approach. a) defining model structure by spatial discretization schemes and hydrological process representations; b) supporting compatible combinations of simulation units and simulation algorithms; and c) enabling the spatial varying allocation and integration of different model structures at the subbasin level.

2.2 Design of the spatially hybrid hydrological modeling approach using the SEIMS framework

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

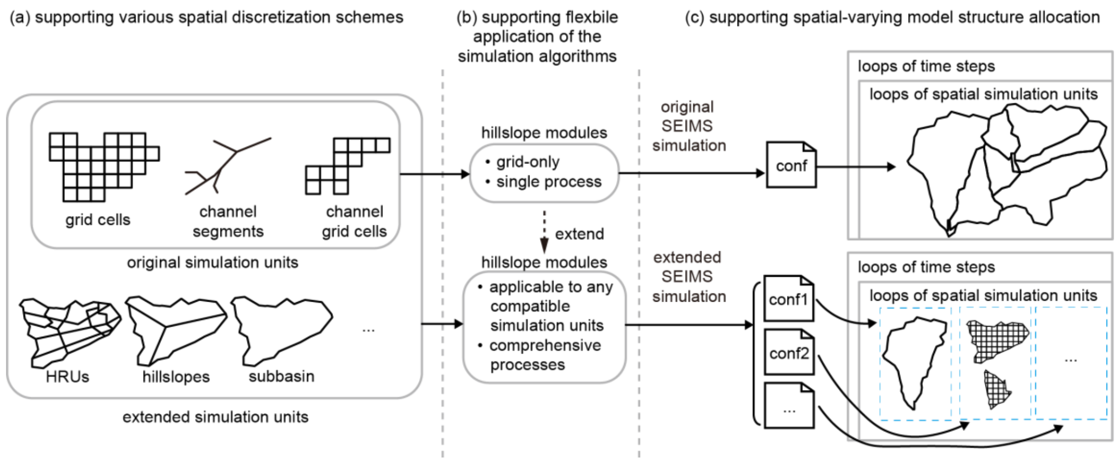

Figure 2. Overall design of extending the SEIMS (Spatially Explicit Integrated Modeling System) to implement the proposed spatially hybrid hydrological modeling approach: a) supporting various spatial discretization schemes; b) supporting applying simulation modules of hillslope processes to compatible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

2.2.1 Brief introduction to SEIMS

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

(1) Spatial discretization scheme

SEIMS primarily adopts a two-level spatial discretization scheme, i.e., the “subbasin–basic simulation unit.” In the stage of preprocessing modeling data, SEIMS delineates the watershed into subbasins, each with one channel. Within each subbasin, the basic simulation units (i.e., grid cells in the original version) are delineated and organized as a one-dimension array. Most simulation modules of hillslope processes use grid cells as simulation units, while a few modules use subbasin units such the linear reservoir algorithm for the groundwater process. Modules of channel routing processes use channel lines or grid cells as simulation units. All parameters required by the modules on these simulation units are prepared using the data preprocessing tools. The grid cells are layered based on the flow direction of each cell (i.e., the single flow direction in the original version; Liu et al., 2014). The layers are used in modules of surface or subsurface flow routing processes to determine the simulation sequences of grid cells. The same idea is used for layering subbasins and channels.

(2) Modular modeling design

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

In SEIMS, each module should handle its required simulation conditions. Users should decide the integration feasibility of the module combinations to meet the requirements of each module, such as the boundary conditions when calculating vertical and lateral water movements. For instance, to implement a semi-physically-based interflow module based on the Darcy's Law, the boundary condition could be set either with the hydraulic gradient equal to the slope at each cell, or dynamically determined using the outputs of adjacent cells provided by other modules.

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

(3) Two-level parallelization strategy

The first level of the two-level parallelization strategy dispatches the simulation of subbasins to different computing processes (or nodes) through the Message Passing Interface (MPI) (Liu et al., 2016). The second level is achieved within each subbasin by dispatching the simulations of grid cells without mutual dependencies to computing threads via Open Multi-Processing (OpenMP) (Liu et al., 2014). Based on the design of the modular structure, variables required to be communicated among subbasins only need to be defined in the metadata of each module and will be handled by the SEIMS main program (Zhu et al., 2019). The two-level parallelization strategy provides the potential to implement the proposed approach in this study that applies different model structures to distinct subbasins.

2.2.2 Constructing model structures with diverse simulation units and algorithms

To enable the flexible construction of model structures based on SEIMS, the diversity of both simulation units and simulation algorithms should be guaranteed. For simulation units, hydrological response units (HRUs) were added as simulation units of hillslope processes in SEIMS, including DominantHRU (defined by dominant combination of soil types, land use types, and slope classes), FullHRU (one HRU may consist of several spatially separated areas), and ExplicitHRU (one HRU is a spatially independent and contiguous area) (Figure 1a; Figure 2a). The physically-based parameters can be derived from actual properties of the soil, landuse/landcover, and other spatial data, while conceptual parameters are directly specified by lookup tables of soil and land-use. For instance, the storage capacity of an HRU can be represented by the soil depth associated with that specific HRU area, while some experimental coefficients could be specified in the lookup tables. Under such an HRU discretization scheme, the hillslope unit and subbasin unit can be regarded as specific DominantHRUs. Therefore, the extended SEIMS will offer the flexibility of utilizing subbasins, hillslopes, HRUs, and grid cells as simulation units of hillslope processes.

For hydrological process representations, SEIMS was initially designed to primarily implement the simulation algorithm of one hydrological process as a single module, while it lacked a conceptual model capable of considering multiple hydrological processes comprehensively (Figure 2b). In this study, lumped conceptual models were designed to be integrated as two separate hillslope modules: (1) a surface runoff module that generate runoff at each basic simulation unit; and (2) a surface routing module that convey runoff to the subbasin outlet. For instance, the representative widely used conceptual model, GR4J (Perrin et al., 2003), is suitable to be incorporated as a surface runoff module, coupled with a separate routing module such as a simple accumulation method. Such a module could be applied to any simulation unit types stated above.

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

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

An essential part of the spatially hybrid hydrological modeling approach is to enable the separate allocation and execution of individual model structures to different subbasins (referred to as subbasin models) within the watershed. All subbasin models are subsequently integrated as a watershed model. The requirements of flexible model configuration and subbasin-separate simulation are compatible with the text-based module configuration method and two-level parallelization strategy of SEIMS, but still need improvement. The module configuration file of SEIMS was extended to designate a model structure to the specific subbasin, and the adopted type of simulation units (Figure 3). In this way, the SEIMS main program was extended to read the configuration file for each subbasin dynamically, load simulation modules, and retrieve the modeling parameters according to the specified basic simulation units.

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

2.3 Implementation

Based on the above method design, the implementation of the proposed approach with SEIMS involves modifications to the data preprocessing tools, SEIMS main programs, and SEIMS module library. The data preprocessing tools mainly include a collection of Python scripts and C++ programs to delineate spatial units at different scales (e.g., subbasins and hillslopes), extract spatial parameters of spatial units, and create watershed modeling database (Zhu et al., 2019). In this study, a configurable tool was implemented to support the delineation and parameterization of HRU-based spatial units. This tool allows users to specify environmental variables (e.g., the default land-use and soil types) to delineate HRU-based units. This tool also allows specifying base spatial units and delineation strategy to generate different types of

HRU such as taking subbasins or hillslopes as base units to generate DominantHRU or FullHRU. Therefore, the data preprocessing tools could prepare various types of spatial unit and associated spatial parameters for each subbasin according to the user-defined configuration file to meet various hydrological modeling scenarios. The procedures of spatially hybrid modeling with SEIMS are depicted in Figure 3.

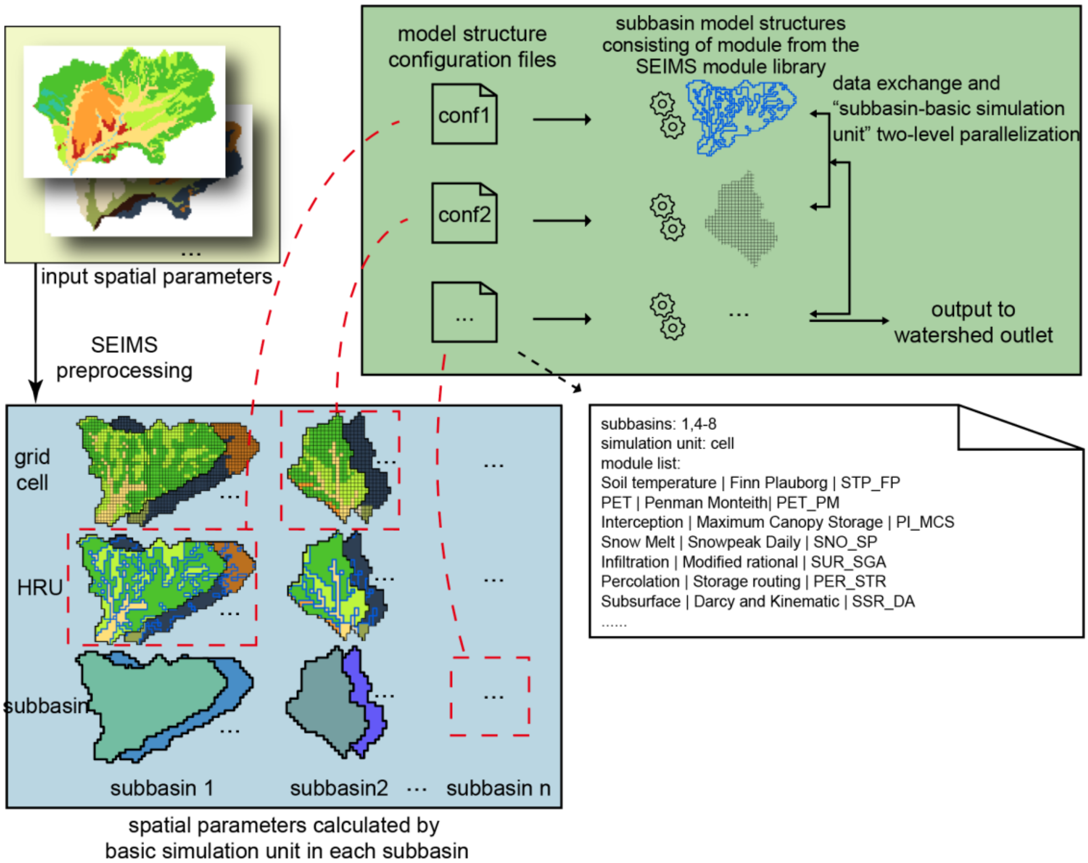

Figure 3. Procedures of spatially hybrid modeling with the SEIMS (Spatially Explicit Integrated Modeling System)

The SEIMS main program, written in C++, was extended to read the configuration file for each subbasin, load simulation modules and retrieve the modeling parameters according to the specified simulation units. Simulation modules of the SEIMS module library were updated to declare the type of computational dependency. New conceptual simulation modules were added such as GR4J for simulating hillslope runoff generation. With the above briefly introduced implementation of the proposed approach, SEIMS can now support users in constructing spatially hybrid model structures for considering spatial heterogeneity of the watershed, where each subbasin may be simulated with different combinations of conceptual or semi-physically-based simulation modules and spatial units. Consequently, more than 40 modules are available after the implementation of this study (detailed in Table S1 of the supplementary material), supporting simulation of processes including snowfall, atmospheric deposition, snow balance, interception, soil temperature, glacier, surface runoff, evapotranspiration, infiltration, percolation, interflow, groundwater, channel routing, plant growth, and soil erosion.

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

3 Case study

3.1 Study area and data

The case study area is the Babao River watershed at Qilian, Qinghai Province, China (Figure 4), a high-altitude, cold and mountainous region with an area of approximately 2,511 km^2. The average elevation is 3,565 m, and the region features glacier, snow cover and frozen soil. The data used in the case study are listed below. The MERIT DEM with the resolution of 90 m (Yamazaki et al., 2017) was selected for watershed delineation and calculation of terrain attributes. Meteorological data was obtained from the China Meteorological Assimilation Driving Datasets for the SWAT model (CMADS) version 1.2, provided in the form of approximately 0.125° resolution gridded station data (Meng et al., 2017). Land cover data was derived from GLOBELAND30 with a resolution of 30 m (http://www.globallandcover.com). Soil attribute data was sourced from the Harmonized World Soil Database (HWSD) Version 2.0 (Nachtergaele, 2023). The observed daily discharge of the outlet gauge from 2013 to 2018 was obtained from the National Hydrological Yearbook.

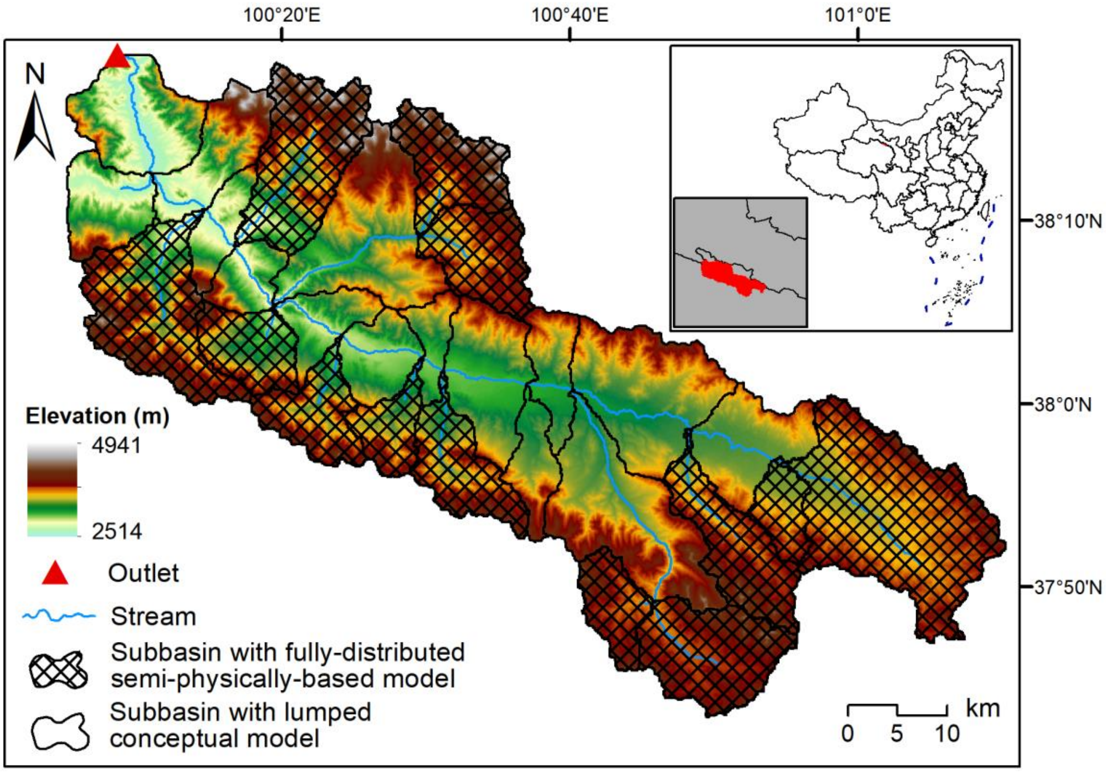

Figure 4. The Babao River watershed and the spatial constitution of the spatially hybrid watershed model.

3.2 Experimental design

To verify the integration feasibility and simulation effectiveness of the proposed spatially hybrid hydrological modeling approach and its implementation using SEIMS, we constructed one fully-distributed semi-physically-based model structure (section 3.2.1) and one lumped conceptual model structure (section 3.2.2) to build one spatially hybrid model and two spatially consistent models (section 3.2.3) for comparison after parameter calibration (section 3.2.4). It is worth noting that the watershed models constructed in this comparative experiment are not intended to model the hydrological processes in the study precisely, nor to enumerate the possible model structures applicable as illustrated in Figure 1.

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

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

Table 1. Simulation algorithms adopted for the fully-distributed semi-physically-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

3.2.2 The lumped conceptual model structure

The lumped conceptual model structure adopts DominantHRUs as the simulation units and GR4J as the main simulation algorithm (Table 2). The Hargreaves method is used to estimate the potential evapotranspiration for the GR4J. The GR4J receives the potential evapotranspiration and precipitation as input to generate the hillslope runoff at the outlet of the simulation unit (i.e., DominantHRUs), which implicitly generalizes the internal surface routing process. The runoff from all DominantHRUs is then aggregated to the subbasin outlet using a simple accumulation method. The inter-subbasin channel routing process is modeled using the Muskingum algorithm. In this case study, each subbasin corresponds to a single DominantHRU, defined by the land cover and soil type combination that occupies the largest area within the subbasin. As a result, GR4J can also be applied without an additional surface routing module.

Table 2. Simulation algorithms adopted for the lumped conceptual model structure 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

3.2.3 One spatially hybrid and two spatially consistent model structures for comparison

Ideally, physically based models can better simulate hydrological processes with explicit physical representations. However, due to practical limitations, such as incomplete understanding of hydrological processes and the difficulty of implementing complex simulation algorithms and deriving essential modeling data, a conceptual model can serve as a valuable complement. In this case study, we constructed a spatially hybrid model structure (referred to as the HybM; Figure 4) by combining both fully-distributed semi-physically-based (see Section 3.2.1) and lumped conceptual models (see Section 3.2.2). We considered the fully-distributed semi-physically-based model structure more suitable for mountainous subbasins (i.e., 13 subbasins shown in Figure 4), while applying the lumped conceptual model structure to gently sloping subbasins (i.e., 16 subbasins shown in Figure 4).

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

3.2.4 Comparative experiments

The comparative experiments primarily aim to assess the post-calibration performance of the three watershed model structures. Parameters for model calibration were chosen through prior sensitivity analyses (listed in Table 1 and Table 2). In principle, the proposed approach adheres to the atomistic forward modeling concept: each subbasin-level model structure should be determined based on the appropriate representation of hydrological processes and available data, ensuring a physically reasonable and practically executable watershed model. Ideally, model calibration should utilize multi-scale observations (e.g., at subbasin and watershed outlets) to avoid relying solely on the inverse calibration assumption that successfully watershed-scale reproduction validates subbasin-scale model structures.

In the absence of multi-scale observations, it is a common practice in current hydrological modeling to calibrate based solely on the watershed outlet data. In this case study, only the watershed outlet discharge data was available. To partially mitigate this limitation, we designed two calibration strategies (i.e., universal and regional). The universal calibration strategy involves a uniform adjustment of parameters for all subbasin models, while the regional calibration strategy applies separate parameter sets to models of mountainous subbasins and gently sloping subbasins. Consequently, the HybM was calibrated using the regional strategy, while both PhyM and ConM were calibrated using both universal and regional strategies (Table 3).

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

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

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

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

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

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

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

The parameter calibration experiments were conducted using the NSGA-II (non-dominated sorting genetic algorithm-II; Deb et al., 2002) integrated in the SEIMS framework (Zhu et al., 2019). The optimization parameters setting for each calibration experiment included a generation of 25 and a population of 360. The multi-objective optimization aimed to maximize NSE and minimize RSR and absolute value of PBIAS. Experiments were carried out on a server equipped with a 2.70 GHz Intel Xeon Gold 6150 dual CPU (36 cores).

3.3 Experimental results and discussion

The integration feasibility of the constructed spatially hybrid watershed model structure is demonstrated by the successful results of the comparative experiments. To evaluate the simulation effectiveness of the proposed approach, one set of calibrated parameters of each experiment (detailed in Table S2 of the supplementary material) was selected for comparison, analyzing both model performance metrics and the hydrographs.

3.3.1 Model performance metrics of calibrated model structures

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

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

The spatially consistent fully-distributed semi-physically-based models (PhyM) exhibited similar NSE (~0.59) and RSR (~0.63) in both calibration and validation periods, regardless of the calibration strategy. However, PhyM1 (universal calibration) yielded a lower PBIAS than PhyM2 (regional calibration). While regional calibration generally allows for more flexible parameter adjustments across heterogeneous subbasins, the higher overall bias observed in PhyM2 may be attributed to the lack of internal subbasin observation data. Without such internal constraints, regional calibration may lead to spatially inconsistent simulation errors that accumulate toward the watershed outlet, thereby increasing the overall bias. In contrast, universal calibration often benefits from compensatory effects among subbasins, resulting in a lower overall bias.

Unlike the effect of calibration strategies on PhyM, the spatially consistent lumped conceptual models (ConM) showed moderate improvements under the regional calibration strategy (ConM2) compared to the universal calibration strategy (ConM1). Specifically, for calibration/validation, the NSE increased from 0.41/0.32 to 0.45/0.50 and the RSR decreased from 0.77/0.82 to 0.74/0.71. For PBIAS, ConM2 yielded 10.96%/-21.03%, showing improved validation bias compared to ConM1 (2.89%/-42.87%), despite a higher calibration-period bias. Conceptual models like ConM, with simple model structure and few parameters, are often considered easier to calibrate and potentially perform better under regional calibration. However, in this study, both ConM1 and ConM2 exhibited relatively low NSE and high RSR values in both periods, indicating the limited capability of the GR4J-based conceptual model structure to represent the hydrological processes in this mountainous watershed, particularly because it does not account for glacier and snowmelt processes. The noticeable decline in validation performance for both ConM1 and ConM2 (e.g., the substantial shift in PBIAS from overestimation to underestimation) further reflects the limited generalization of ConM. The contrasting results between ConM and PhyM may be attributed to their structural differences in handling spatial variability. ConM relies more on regional calibration to consider spatial heterogenous across subbasins by adjusting its less physically constrained parameters. In contrast, PhyM captures spatial heterogeneity directly through spatially distributed input data and parameters, implying a low dependency on calibration strategies to represent spatial variations in hydrological processes.

The spatially hybrid model structure (HybM) demonstrated a balanced model performance by leveraging the strengths of both PhyM and ConM, achieving the highest NSE (0.72/0.60) and lowest RSR (0.53/0.63) among all experimental cases. However, its PBIAS (10.02%/-18.28%) was lower than (i.e., better overall bias) that of both ConM cases but higher than (i.e., worse overall bias) both PhyM cases. This reflects that the spatially hybrid model structure provides a promising compromise between modeling flexibility and simulation accuracy. That is, while HybM combined the calibration responsiveness of ConM and the process realism of PhyM, it also inherited some of their respective limitations, such as bias associated with the conceptual representation. Overall, these findings highlight the importance of careful model structure construction and the necessity of multi-site and long-term observation data to effectively constrain calibration and fully realize the benefits of the proposed approach.

3.3.2 Hydrographs of calibrated model structures

Figure 5 compares the outlet hydrographs simulated by PhyM1, ConM2, and HybM against the observed discharge. During the dry seasons (typically November to April), when baseflow dominates streamflow, PhyM1 better simulates baseflow magnitudes, benefiting from its process-based representation of hydrological processes. In contrast, ConM2 tends to overestimate baseflow, likely due to its simplified recession formulation and lack of explicit representation of groundwater storage and release dynamics. During the wet season, characterized by high-intensity precipitation events, PhyM1 produces sharper rising and falling limbs, generally capturing the dynamics of observed peaks and recessions. This behavior reflects the physical realism of PhyM in representing rapid surface and subsurface responses in the study area. Conversely, ConM2 often either overestimates or underestimates peak flows, likely due to limitations in its conceptual routing and storage structure.

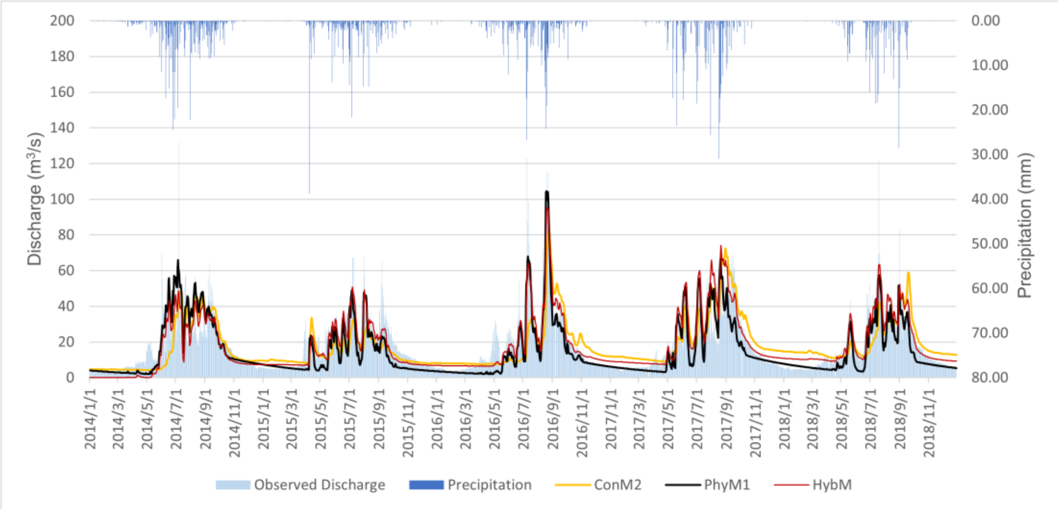

Figure 5. Simulated outlet hydrographs of best-performing cases for each model structure: PhyM1 (fully-distributed semi-physically-based model structure using universal calibration strategy), ConM2 (lumped conceptual model structure using regional calibration strategy), and HybM (spatially hybrid model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

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

4 Discussion

The case study results have demonstrated the integration feasibility and simulation effectiveness of the proposed spatially hybrid hydrological modeling approach. The results reflect an inherent trade-off in this approach, that is, enhanced flexibility and local adaptability often come at the cost of increased structural complexity and potential uncertainty. Nevertheless, the proposed approach offers a practical and adaptable framework to address spatial heterogeneity in diverse hydrological modeling application contexts, particularly where data availability and watershed characteristics vary across space. This section further discusses its broader implications, focusing on the significance of the advantages of SEIMS in implementing the proposed approach and limitations and future directions.

4.1 Advantages of SEIMS in implementing the proposed approach

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

SEIMS's design enables model developers to reuse or adapt existing model codes as SEIMS modules to simulate individual or multiple hydrological processes. For instance, the GR4J module was adapted from the Raven framework (Craig, 2020). Newly developed modules can be flexibly combined with existing ones to construct various model structures. This capability is particularly valuable for large and heterogeneous watersheds where modeling application contexts vary across regions. For instance, in subbasins with limited spatial data, lumped conceptual components can be employed in place of data-intensive distributed model structures to ensure model feasibility. It is worth noting that while SEIMS provides this flexibility, module developers are responsible for specifying input requirements and boundary conditions for their modules, and users should assess the hydrological rationality and integration feasibility of their combined model structure.

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

4.2 Limitations and future directions

This section highlights key limitations and outlines future directions to enhance its practical applicability. First, the successful application of the proposed approach implemented within SEIMS largely depends on the breadth and quality of its module library. Though extensible, the module library lacks modules for several critical hydrological processes (e.g., frozen soil dynamics) and specific representations (e.g., fully-physically-based simulation algorithms that tightly couple hillslope hydrological processes). Recent research efforts continue to expand SEIMS module library to support more complex hydrological processes, for instance, by modeling groundwater–surface water interactions between alpine runoff and alluvial aquifers in high mountain watersheds (Liu et al., 2025). We plan to gradually implement a variety of fully-physically-based simulation modules, such as a 2D hillslope overland flow module inspired by FullSWOF (Full Shallow-Water equations for Overland Flow; Delestre et al., 2017), and a fully coupled 3D module of overland flow, subsurface flow, and groundwater flow following approaches from SHUD (Shu et al., 2020) and ParFlow (Kollet and Maxwell, 2006). We encourage model developers to contribute to the enrichment of the SEIMS module library, either by transplanting existing code or developing new modules based on established hydrological equations and the SEIMS module template.

Second, while the subbasin-independent architecture of SEIMS is a key feature to implement the proposed approach, it also raises concerns about inter-subbasin connectivity for more complex modeling circumstances. For instance, when multiple flow direction algorithms are used to construct the hillslope flow routing network, flow paths may cross subbasin boundaries and the connectivity between subbasins becomes more frequent than only connected by the channel network. Future work should explore flexible inter-subbasin connectivity mechanisms to consider more realistic hydrological interactions across subbasins. Besides, while the inter-subbasin coupling operates at a consistent subbasin scale through the same or different channel routing algorithms, this study did not explicitly address the coupling of processes across nested spatial and temporal scales within each subbasin and the transfer of uncertainties between them, which remains central challenges in hydrology community. The proposed approach and the implemented modeling framework are extensible to support such research in the future.

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

Fourth, the current case study was designed as a simplified proof-of-concept application to demonstrate the methodological feasibility of the proposed approach. Nevertheless, more comprehensive case studies in watershed with multi-scale observed data and diverse climatic, topographic, and landuse conditions are needed to further evaluate the robustness, generalizability, and uncertainty implications of the proposed approach. For instance, future applications should incorporate uncertainty analysis frameworks to better understand and quantify the trade-offs between modeling flexibility and simulation accuracy.

5 Conclusion

This study proposed a new spatially hybrid hydrological modeling approach to address the challenge of representing spatial heterogeneity in complex hydrological modeling application contexts. Adopting a divide-and-conquer strategy, the approach allows for flexible combination of compatible spatial discretization schemes (i.e., simulation units) and hydrological process representations (i.e., simulation algorithms) across subbasins. This approach provides a pragmatic and flexible modeling solution to enable the integration of existing hydrological modeling methods at the subbasin scale.

The approach was implemented within the SEIMS framework, leveraging its modular, subbasin-independent architecture and parallel computing capabilities. Comparative experiments in a medium-sized watershed demonstrated its integration feasibility and simulation effectiveness. The spatially hybrid model structure successfully combines the strengths of both spatially consistent model structures, improving general performance, while also inheriting some limitations from its constituent components. The experimental results highlight its capability to balance modeling flexibility and simulation accuracy under heterogeneous watershed conditions.

This study does not intend to resolve the fundamental hydrological issues such as the scaling issues (Dooge, 1986; Beven, 2000), nor to ignore their existence, but rather to provide a practical and extensible framework for hydrological modeling across diverse application contexts. The proposed approach and its implementation are extensible through the reuse and integration of existing model efforts, thus holding the potential to support investigations into these theoretical issues as new theories and data become available. Moreover, this study lays the groundwork for future research on knowledge-driven intelligent modeling methods and tools for complex watershed modeling and management in spatially heterogeneous environments.

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CRediT authorship contribution statement

Yu-Jing Wang: Writing – original draft, Software, Methodology, Investigation. **Liang-Jun Zhu**: Writing – original draft, Writing – review & editing, Software, Methodology, Investigation, Funding acquisition, Conceptualization. **Cheng-Zhi Qin**:

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