 

# A spatially hybrid hydrological modeling approach based on spatial heterogeneity of watershed characteristics

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**Abstract**:

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

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

Highlights (3 to 5 bullet points (maximum 85 characters including spaces per bullet point)

# Highlights

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

# 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 watershed characteristics, available data, and other related factors (Beven, 2000; Gharari et al., 2021; Wagener et al., 2001). Hydrological models can be classified from two perspectives that define their model structures: the spatial discretization scheme (such as lumped and semi- or fully-distributed models) and the representation of hydrological processes (such as conceptual and semi- or fully-physically-based models) (Chow, 1988; Milad et al., 2012; Dingman, 2015; Hrachowitz and Clark, 2017). The determination of an application-specific model structure, involving the decision of the appropriate spatial discretization scheme and hydrological process representations, stands as the primary and critical step in hydrological modeling (Butts et al., 2004; David et al., 2022; Pilz et al., 2020; van Esse et al., 2013).

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

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

The representation of hydrological processes denotes the simulation algorithms of real-world hydrological phenomena (e.g., evaporation, infiltration, and surface and subsurface flow routing) through mathematical equations, numerical solutions, and spatiotemporal discretization. Conceptual representations simplify hydrological processes within a watershed into a few lumped components, typically including water storage, water losses, and flow routing. They are often implemented using conceptual reservoirs (or buckets), such as linear method or two-reservoir method for runoff prediction. Parameters in conceptual models often lack explicit physical interpretation and are typically estimated via calibration (Fenicia et al., 2011; Knoben et al., 2019). In contrast, fully-physically-based representations apply fundamental physical laws to simulate the conservation of mass, momentum, and energy in both vertical and lateral directions (Abbott et al., 1986). This is commonly achieved by solving coupled partial differential equations, such as the Richards' equation for unsaturated flow and Saint-Venant equations for surface flow, as implemented in models like MIKE SHE (Système Hydrologique Europeén; Graham and Butts, 2005). While offering high-fidelity representations of hydrological processes, they often involve extensive data requirements and high computational complexity. To address the trade-off between physical realism and computational feasibility, semi-physically-based representations employ simplified physical equations for individual hydrological processes while avoiding full numerical coupling. These processes are generally simulated independently. Although empirical components may be included, most model parameters retain clear physical interpretations and often can be estimated from field observations. A prominent example utilizing semi-physically-based representations is SWAT (Arnold et al., 1998). In this study, we primarily focus on the conceptual and semi-physically-based representations.

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 spatial units (also referred to as simulation units) and simulation algorithms for hydrological processes are the same for the whole watershed. Most research on directly choosing a single existing hydrological model with a fixed or near-fixed model structure falls into this category. Such model structures are often developed with specific assumptions and suitable for constrained application contexts. They vary from lumped to fully-distributed spatial discretization schemes, and from conceptual to fully-physically-based representation of hydrological processes. Based on the most typical configuration or usage of each model, examples include: the lumped and conceptual HBV (Hydrologiska Byråns Vattenbalansavdelning; Lindström et al., 1997) and GR4J (modèle du Génie Rural à 4 paramètres Journalier; Perrin et al., 2003); the semi-distributed and semi-physically-based TOPMODEL (TOPography based hydrological MODEL; Beven and Kirkby, 1979), SWAT, and RHESSys (Regional Hydro-Ecologic Simulation System; Tague and Band, 2004); the fully-distributed and semi-physically-based DHSVM (Distributed Hydrology Soil Vegetation Model; Wigmosta et al., 1994); and the fully-distributed and fully-physically-based MIKE SHE. Adopting a spatially consistent model structure inherently assumes that the spatial variability of watershed characteristics can be adequately captured by the input data and parameters required by the chosen model structure. Nevertheless, a fixed or near-fixed model structure often lacks flexibility in adapting simulation units and incorporating alternative simulation algorithms for considered hydrological processes. For example, models that rely solely on the infiltration-excess runoff mechanism are unsuitable for watersheds where saturation-excess runoff dominates. Therefore, using a rigid model structure may fail to effectively accommodate diverse and complex application contexts (Ley et al., 2016; Savenije, 2009).

To address the limitations of fixed model structure and accommodate complex application contexts with greater flexibility in determining the model structure, researchers have increasingly turned to modular hydrological modeling frameworks, such as SUMMA (Structure for Unifying Multiple Modeling Alternatives; Clark et al., 2015), ECHSE (ECo-Hydrological Simulation Environment; Kneis, 2015), MARRMoT (Modular Assessment of Rainfall–Runoff Models Toolbox; Knoben et al., 2019), SEIMS (Spatially Explicit Integrated Modeling System; Liu et al., 2016; Zhu et al., 2019), and Raven (Craig, 2020). These frameworks emphasize various aspects of flexibility in customizing application-specific model structures, including extensible types of simulation units and associated simulation algorithms (Kneis, 2015), alternative simulation algorithms for individual hydrological processes (Zhu et al., 2019), and alternative simulation algorithms for each conceptual component of hydrological processes (Craig, 2020). By supporting the concept of “multiple working hypotheses” (Clark et al., 2011), these frameworks facilitate studies on the suitability and uncertainty of alternative model structures (David et al., 2022; Kiraz et al., 2013;

Knoben et al., 2020). However, the primary focus of these frameworks remains on customizing and applying a spatially consistent model structure across the entire watershed. This spatial consistency may be unreasonable and inaccurate to capture the dominant hydrological processes in application contexts exhibiting significant spatial heterogeneity (Gao et al., 2018; 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., 2021b) 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 or near-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., 2023). 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. Nevertheless, these frameworks are fundamentally limited to conceptual representations of hydrological processes, with simulation units typically being subbasins, DominantHRUs, or FullHRUs. 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, such as grid cells, where spatial relationships between units are maintained to enable the execution of physically-based simulation algorithms. This limitation also constrains the exploration of suitable perceptual models for specific applications (Beven, 2012; Wang et al., 2021a).

To address the inability of existing hydrological modeling frameworks to support spatially varying distributed physically-based model structures, this paper proposes a new and practically significant spatially hybrid modeling approach. In this approach, compatible types of simulation units and simulation algorithms can be combined to construct different model structures for each subbasin within the watershed, such as lumped conceptual, lumped semi-physically-based, semi-distributed semi-physically-based, and fully-distributed semi-physically-based model structures. Subbasin-level model structures can then be integrated to perform the watershed-scale simulation.

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

The core concept for designing flexibly constructed model structure involves decoupling hydrological process representations (i.e., simulation algorithms) from specific spatial discretization scheme (i.e., simulation units). For instance, the physically-based algorithms are typically applied to fine-scale units such as grid cells, for both are assumed to describe the hydrological process in detail. Similarly, conceptual algorithms are typically associated with lumped or coarse-scale units such as DominantHRUs, hillslopes, or subbasins. However, this rigid binding is not always necessary. Conversely, combining different model structure components has proven effective, as evidenced by various studies (Gunduz and Aral, 2005; Liu et al., 2020; Sidle, 2021). Simulation algorithms can be classified as computationally dependent and computationally independent based on their inter-unit computational dependency. The simulation of a computationally dependent algorithm on one simulation unit often relies on the water flows or state variables of its adjacent or upstream units, whereas a computationally independent algorithm simulates independently for each unit (Figure 1b). Similarly, simulation units can be categorized as spatially connected and spatially disconnected depending on whether spatially explicit relationships exist between units (Figure 1a).

Therefore, three compatible combinations of simulation algorithms and simulation units can be identified: 1) computationally dependent algorithm with spatially connected units, 2) computationally independent algorithm with spatially connected units, and 3) computationally independent algorithm with spatially disconnected units (Figure 1b). For instance, a conceptual reservoir-based surface runoff generation algorithm integrated 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 integration 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), requiring no computational dependency. It is crucial to note that while computational dependency is a fundamental constraint, the ultimate rationality of a chosen model structure relies on the modeler's hydrological knowledge and specific application requirements.

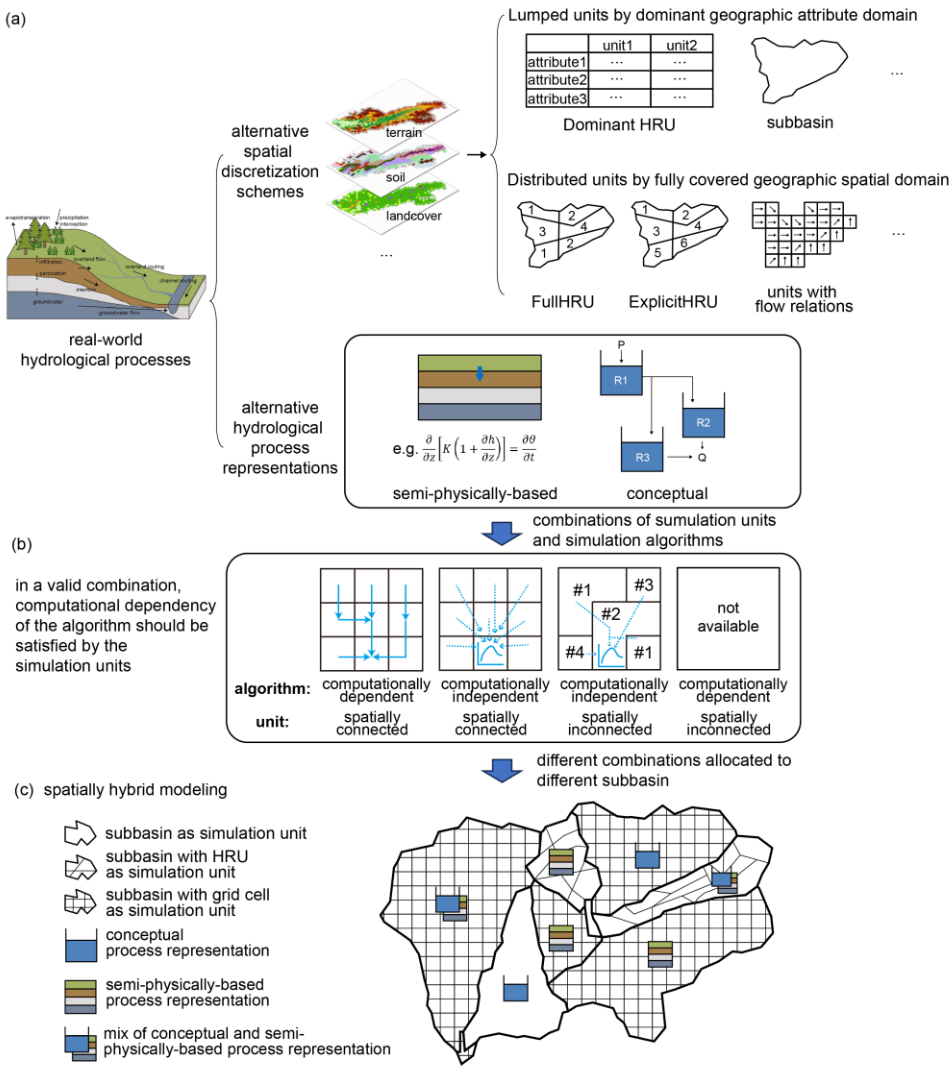


Figure 1. Design of the proposed spatially hybrid hydrological modeling approach. a) decoupling the simulation of hydrological processes into spatial discretization schemes and hydrological process representations; b) supporting compatible combinations of simulation algorithms and simulation units; and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

Based on the above idea of flexible model structure construction approach, this study considers the spatial heterogeneity of watershed characteristics by treating each subbasin unit as the modeling unit. Each subbasin is configured with an individual subbasin model structure to simulate hillslope processes, which are then integrated into a comprehensive watershed model via channel routing processes (Figure 1c). A subbasin model structure can either encompass all hydrologic process holistically or, more commonly, separately consider hillslope processes and the channel routing process. Therefore, different subbasin model structures can be constructed, such as conceptual algorithms with subbasin as simulation unit, semi-physically-based algorithms with grid cells as simulation units, and a mix of conceptual and semi-physically-based algorithms with HRU as simulation units for hillslope process and a conceptual algorithm for the channel routing process (Figure 1c). Since it is assumed in this study that mass and energy only exchange between subbasins through channel routing, all subbasin model structures collectively form the overall watershed model structure by interconnecting through the drainage network with upstream-downstream relationships. The execution of a downstream subbasin relies on the output of its upstream subbasins. This dependency implies that subbasin executions without upstream-downstream relationships can be parallelized, while those with dependencies must be executed sequentially.

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

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 model structure construction of the proposed approach, the spatial discretization schemes of SEIMS should be expanded (Figure 2a; Section 2.2.2), the simulation modules of hillslope processes should be upgraded to accommodate compatible simulation units (Figure 2b; Section 2.2.2), and the execution of SEIMS-based model should be upgraded to allocate different model structures to subbasins and executed in an integrated way (Figure 2c; Section 2.2.3).

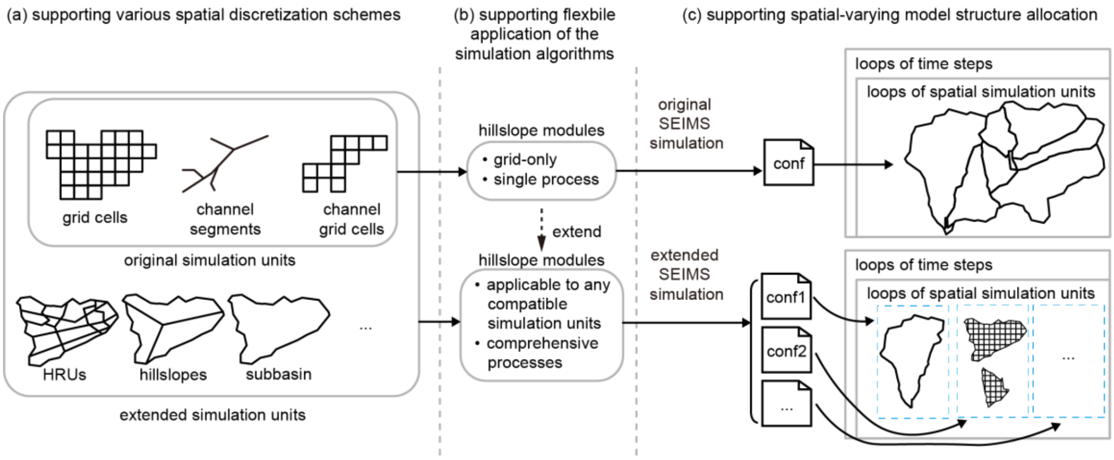


Figure 2. Overall design of extending the SEIMS (Spatially Explicit Integrated Modeling System) to implement the proposed spatially hybrid hydrological modeling approach: a) supporting various spatial discretization schemes; b) supporting applying simulation algorithms of hillslope processes to compatible simulation units; and c) supporting spatial varying model structure allocation on the subbasin level 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 the developing principles. The principles are briefly introduced in three aspects: the spatial discretization scheme, the modular modeling design, and the parallelization strategy.

**(1) Spatial discretization scheme**

SEIMS 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 with their actual positions recorded. 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 preprocessing scripts of SEIMS. The grid cells are layered within each subbasin 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 hillslope 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 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, including 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 by the outputs of modules from adjacent subbasins.

Each module inherits from a standard module interface, including the definitions of input data, parameters, and output data. 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**

Since SEIMS treated subbasins as relatively independent modeling units for hydrological modeling, 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). That means the complicated MPI programming details are hidden from module developers. Besides, the implementation of OpenMP-based parallelization only needs one line of preprocessor directive code before the loop of computationally independent code. Therefore, module developers can develop modules and build high-performance hydrological models in a nearly serial programming way (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, the idea of constructing hydrological response units (HRUs) could be added as simulation units of hillslope processes in SEIMS, including DominantHRU, FullHRU, and ExplicitHRU (see the Introduction section for details; Figure 1a) (Figure 2a). In terms of parameters, 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 reservoir 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 DominantHRU to be used as simulation units. Therefore, the extended SEIMS will offer the flexibility of utilizing subbasins, hillslopes, HRUs, and grid cells as simulation units of hillslope processes for various modeling needs.

For hydrological process representations, SEIMS was initially designed to primarily integrate simulation algorithms of one hydrological process into each single module, while it lacked a conceptual model capable of considering multiple hydrological processes comprehensively (Figure 2b). To bridge this gap, lumped conceptual models can 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 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 should be extended to mark its computational dependency requirement as computationally dependent or independent. 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 the 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 should be extended to designate a model structure to the specific subbasin, and the adopted type of basic simulation units (Figure 3). In this way, the SEIMS main program can 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 should be 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 should be 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 is depicted in Figure 3.

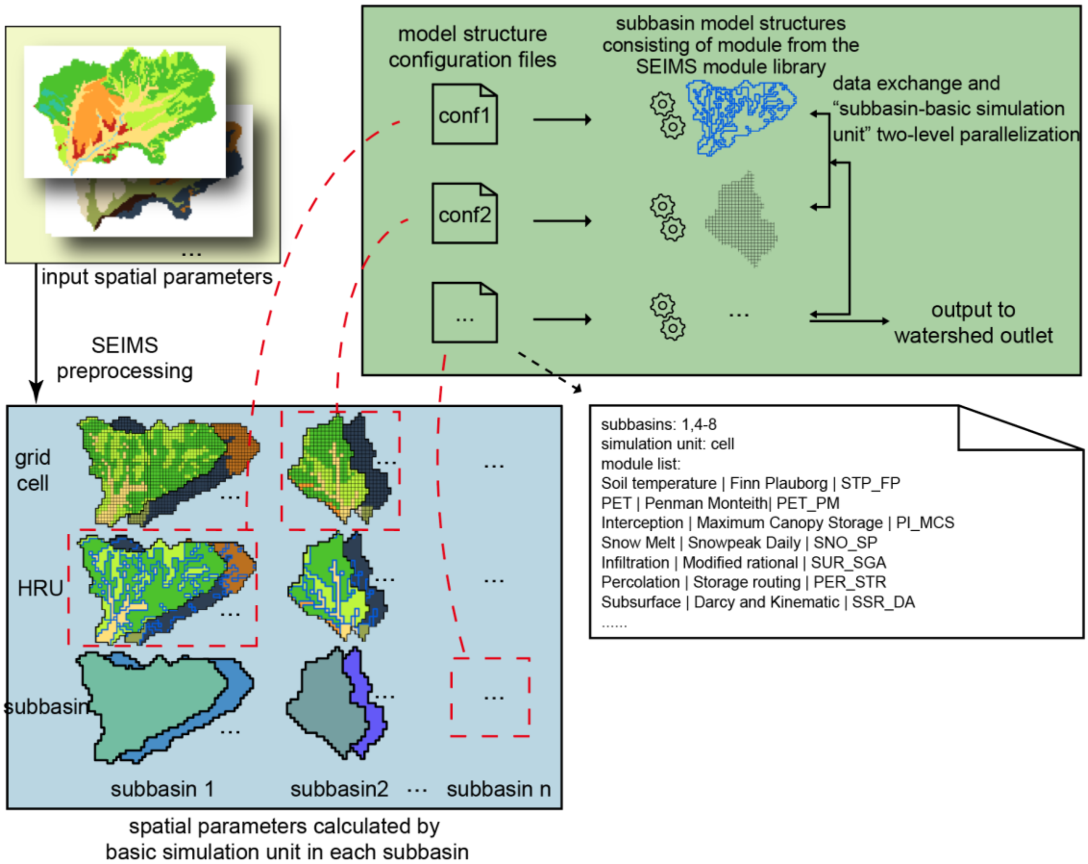


Figure 3. Procedures of spatially hybrid modeling with the SEIMS (Spatially Explicit Integrated Modeling System)

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, 42 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

In this study, we selected the Babao River watershed at Qilian, Qinghai Province, China (Figure 4) as the case study area to verify the proposed approach through daily runoff simulation. It is located in 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., 2019). 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 is obtained from the National Hydrological Yearbook.

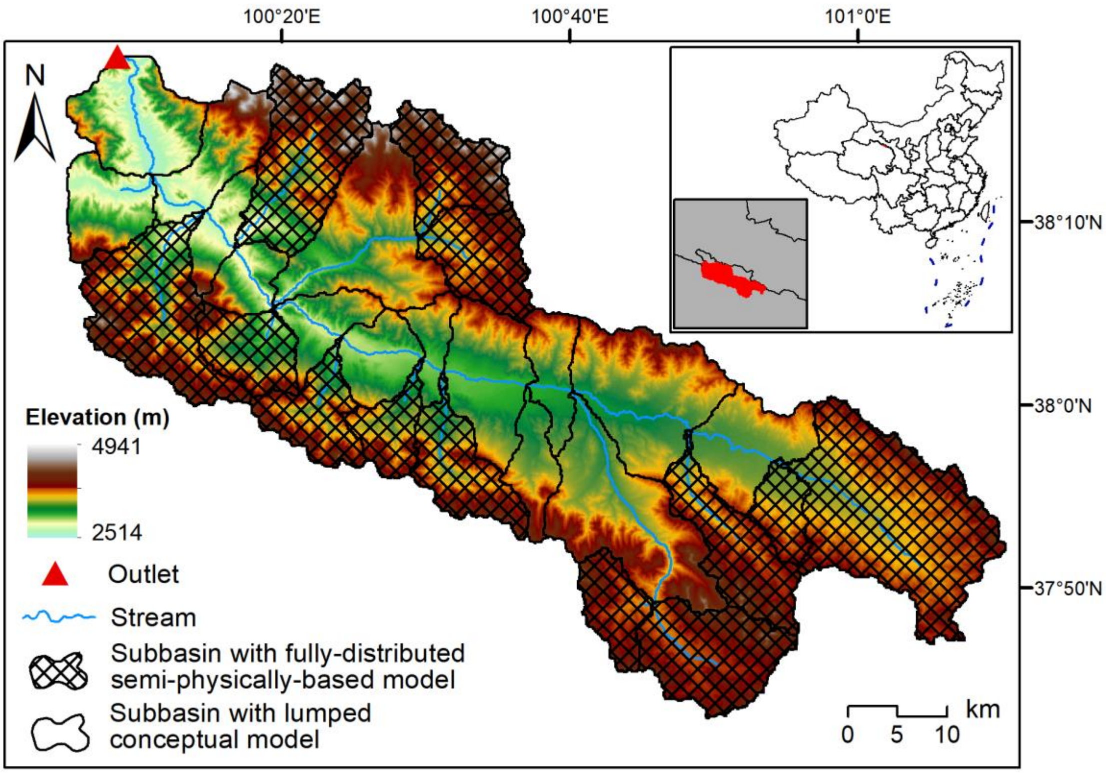


Figure 4. The Babao River watershed and the spatial constitution of the spatially hybrid watershed model.

## 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 listed 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 and leaf area index. 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 generalizing 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, assuming flow transfer only occurs between the outlet points of adjacent upstream-downstream subbasins. 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, 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 (listed in Table 1 and Table 2) were chosen through prior sensitivity analyses. For HybM, a regional calibration strategy was used: parameters of subbasins with the same model structure (either fully-distributed semi-physically-based or the lumped conceptual) were adjusted together (i.e., added or multiplied an adjustment value). This means mountainous subbasins shared one set of calibrated parameters, and gently sloping subbasins shared another (Figure 4). To compare with HybM, both PhyM and ConM were calibrated using two strategies: 1) universal calibration, where parameters of all subbasins were adjusted uniformly; and 2) regional calibration, the same strategy used for HybM. All calibration experiments are detailed in 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).

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

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

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

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 successful execution of the constructed spatially hybrid watershed model structure demonstrates the integration feasibility of different subbasin-level model structures in a spatially varying manner. 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 (only outlet discharge was available in this case study). 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 that the GR4J-based conceptual model structure has limited ability to represent the hydrological processes in this watershed. 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 4 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 accurately 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, closely matching 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.

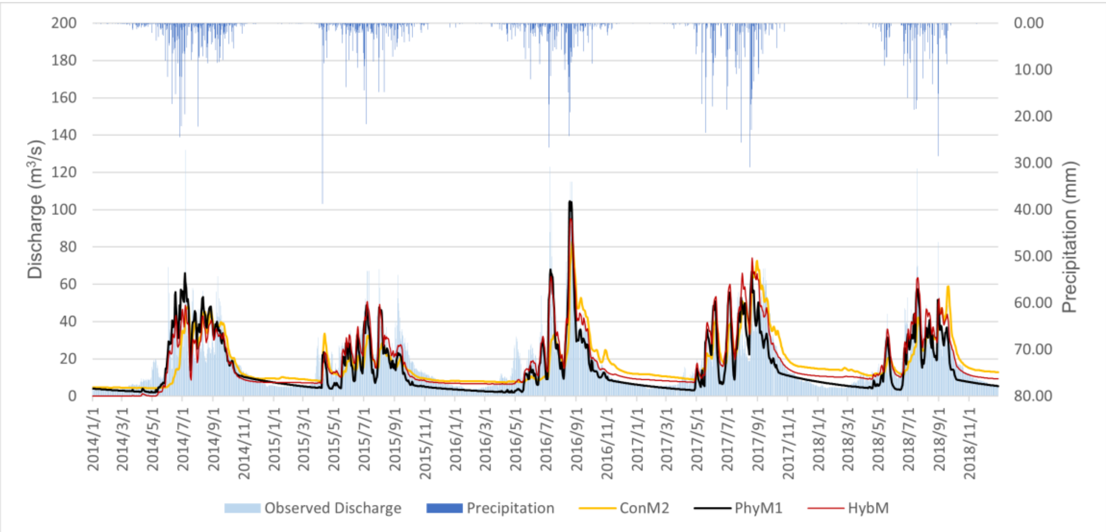


Figure 4. Simulated outlet hydrographs of best-performing cases for each model structure: PhyM1 (fully-distributed semi-physically-based model structure using universal calibration strategy), ConM2 (lumped conceptual model structure using regional calibration strategy), and HybM (spatially hybrid model 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.

Overall, these results illustrate the benefits of spatially combining different model structures. The proposed approach offers enhanced flexibility to accommodate diverse application contexts and demonstrates promising improvements in general hydrograph accuracy.

# 4 Discussion

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

## 4.1 Significance of the spatially hybrid modeling approach

The case study results confirmed the methodological validity of spatially combining different model structures within a watershed. The spatially hybrid model structure (HybM) constructed in this case study achieved highest performance in terms of NSE and RSR. However, it also inherited limitations from its constituent model structures, such as higher PBIAS from the lumped conceptual model structure

(ConM). This reflects an inherent trade-off in spatially hybrid modeling, that is, enhanced flexibility and local adaptability often come at the cost of increased structural complexity and potential uncertainty. Despite these limitations, 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.

It should be noted that this case study was designed primarily to demonstrate methodological feasibility, relying on a simplified application context and data-driven model calibration. Future research should place more emphasis on integrating domain knowledge-driven with data-driven methods to formalize complex application contexts, identify appropriate spatially hybrid model structures, and constrain model calibration using expert knowledge and modeling experience from similar case studies (Qin et al., 2025).

## 4.2 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.

## 4.3 Limitations and future directions

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

First, the successful application of the current implementation largely depends on the breadth and quality of the SEIMS 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 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 channel network. Future work should explore flexible inter-subbasin connectivity mechanisms to consider more realistic hydrological interactions across subbasins.

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, while the current case study is sufficient to demonstrate the integration feasibility and simulation effectiveness of the proposed approach, its application context remains relatively simplified. More comprehensive case studies across diverse watersheds (e.g., with varying climatic, topographic, and data conditions) are needed to evaluate the robustness, generalizability, and uncertainty implications of the spatially hybrid modeling 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 watersheds.

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.

The approach was implemented within the SEIMS hydrological modeling framework, leveraging its modular, subbasin-independent architecture and parallel computing capabilities. Comparative experiments in a medium-sized watershed demonstrated the integration feasibility and simulation effectiveness of the proposed approach. Specifically, the spatially hybrid model structure successfully combines the strengths of both spatially consistent model structures, achieving improved general performance. While the hybrid model structure also inherently inherits some limitations from its constituent components (e.g., simulation bias from the conceptual model structure). The experimental results highlight its capability to balance modeling flexibility and simulation accuracy under heterogeneous watershed conditions.

The proposed approach offers a practical and extensible framework for hydrological modeling across diverse application contexts. By enabling the reuse and integration of existing model efforts, the proposed approach facilitates efficient model development and customization. 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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