

# Twenty Years of Trials and Insights: Bridging Legacy and Next Generation in ParFlow and Land Surface Model Coupling

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## Abstract

Groundwater plays a vital role in terrestrial water and energy cycles. Yet, it remains oversimplified in most Earth system models (ESMs), limiting their ability to represent key land-atmosphere interactions, including evapotranspiration partitioning, drought propagation, and boundary layer development. The original coupling of ParFlow with the Common Land Model (CoLM) in 2005 not only demonstrated the feasibility of integrating physically based groundwater models into ESMs, but also revealed emergent behaviors—such as lateral moisture redistribution, along with the buffering effects that emerge from enhanced subsurface connectivity—that cannot be captured by traditional land surface models (LSMs). This study reviews key findings from two decades of ParFlow–land/atmosphere coupled modeling efforts, highlighting how groundwater–land–atmosphere interactions shape surface energy balance and hydrologic connectivity across three dimensions: upward feedbacks, downward influences, and the critical zone of coupling. Given the substantial advances in LSMs such as CoLM over the past two decades, a renewed recoupling effort is warranted to enhance our understanding of groundwater’s role across a broader range of Earth system processes. Preliminary efforts to recouple ParFlow with the updated water and energy modules of CoLM demonstrate improved performance when evaluated against reanalysis and observational data. To ensure long-term sustainability, we propose a modular and maintainable coupling framework addressing functional extensibility, data/code interoperability, and parallel computing needs, in which area, TerrSysMP2 has taken early steps and may be considered an initial forerunner. Finally, we summarize existing ParFlow-based coupled systems and highlight the need for a community-led model intercomparison project (PLCMIP) to benchmark performance, evaluate process coupling under varied configurations, and foster cross-community collaboration.

## 42 1. Introduction

43 In 2005, Maxwell and Miller published "*Development of a Coupled Land Surface and*  
44 *Groundwater Model*" in *Journal of Hydrometeorology* (Maxwell and Miller, 2005). Their work  
45 introduced the first coupling of ParFlow (Ashby and Falgout, 1996; Jones and Woodward, 2001)  
46 and the Common Land Model (CLM) (Dai et al., 2003), and validated the framework using both  
47 synthetic and real-world test cases. The study highlighted the importance of groundwater  
48 representation in land surface processes (Fan et al., 2019; Zeng et al., 2018; De Graaf and  
49 Stahl, 2022; Seuffert et al., 2002). In particular, it emphasized the role of lateral subsurface flow  
50 (Figure 1), a component that was not explicitly represented in most land surface models (LSMs)  
51 at the time. This work represented an early step toward incorporating physically based  
52 groundwater dynamics into Earth system modeling frameworks.

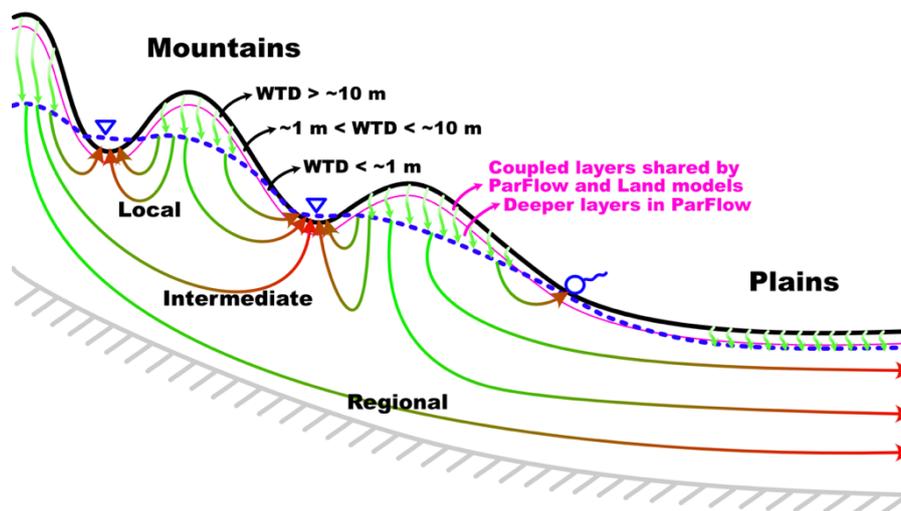
53 Since LSMs serve as the lower boundary in ESMs, this coupling provided a practical  
54 pathway to incorporate groundwater dynamics into larger-scale Earth system frameworks.  
55 Compared to earlier coupling attempts based on tightly integrated or proprietary platforms (Yeh  
56 and Eltahir, 2005; Ivanov et al., 2004; York et al., 2002), this effort leveraged established  
57 community models and an open design philosophy, facilitating broader applicability and long-  
58 term adaptability. The resulting ParFlow-CLM model and other subsequent models coupled  
59 with ParFlow have been applied in a range of hydrological and land-atmosphere studies  
60 (Maxwell et al., 2007; Maxwell et al., 2011; Shrestha et al., 2014), contributing to improved  
61 understanding of water and energy exchanges across subsurface, land surface, and  
62 atmospheric domains (Rahman et al., 2015; Sulis et al., 2017; Keune et al., 2016; Forrester  
63 and Maxwell, 2020). Even today, groundwater-land surface coupling remains underutilized in  
64 many large-scale modeling frameworks, where groundwater models are often run offline with  
65 limited interaction with land-atmosphere processes (De Graaf et al., 2017; Reinecke et al.,  
66 2019; Verkaik et al., 2022), thereby missing dynamic feedbacks with the land-atmosphere  
67 system.

68 The groundwater model, ParFlow, simulates fully 3D variably saturated subsurface flow  
69 and overland flow by integrating Richards' equation with the shallow water equation in a unified  
70 numerical framework (Kollet and Maxwell, 2006; Osei-Kuffuor et al., 2014; Maxwell, 2013).  
71 Meanwhile, the Common Land Model (CLM, now CoLM) captures water and energy processes  
72 from the canopy top to the bottom of the root zone. These two models were coupled through  
73 the root zone (Figure 1), where net fluxes from CoLM after the interactions of infiltration and  
74 evapotranspiration (ET) are treated as source/sink terms in ParFlow, while ParFlow returns soil  
75 moisture and pressure head to CoLM to close the water and energy balance. Such a coupling  
76 approach in terms of physics has been widely adopted by the following coupling works (Niu et  
77 al., 2014; Fang et al., 2022; Maina et al., 2025).

78 After two decades of continuous development, LSMs such as CoLM have seen substantial  
79 advancements in functionality, code architecture, data structures, I/O systems, pre-/post-  
80 processing tools, and high-performance computing capabilities. ParFlow has undergone similar

81 progress on the hydrological modeling front (Kuffour et al., 2020). Although the original coupling  
82 between ParFlow and CoLM was once considered sustainable, it is now increasingly  
83 inadequate as both models continue to grow in complexity and scope.

84 At this twenty-year juncture, it is necessary to re-examine the current state of the coupled  
85 system and clarify how the next stage of development should proceed. This involves, first,  
86 synthesizing the scientific findings enabled by the coupled framework over the past two  
87 decades to fully understand its importance for groundwater–land–atmosphere interactions. It  
88 also requires an initial assessment of the new coupling—particularly its physical functionality  
89 and performance—to clarify the benefits of moving forward. Finally, it is essential to consider  
90 how future recoupling can be made sustainable. Together, these steps will support a cross-  
91 disciplinary effort that provides a robust platform for the broader community to apply coupled  
92 models efficiently, pursue advanced Earth system questions, and strengthen collaborative  
93 research. Here we take CoLM as an example to present this transitional effort.



94  
95 **Figure 1. Illustration of the lateral groundwater flow, the critical zone of water table depth,**  
96 **and the coupling strategy between ParFlow and land surface models. Modified from**  
97 **Yang et al. (2023).**

98 In this paper, we begin by reviewing key insights gained from two decades of research  
99 involving ParFlow-based coupled modeling systems. Building on this foundation, we highlight  
100 how increasing model complexity and functionality are driving a shift toward a next-generation  
101 coupling paradigm. We then present a re-coupling of the latest versions of ParFlow (PF) and  
102 CoLM, focusing on core functionalities of CoLM to demonstrate feasibility and highlight  
103 improvements in overall model performance. This science-oriented integration of basic  
104 modules—built upon the original coupling interface—serves as a foundation for broader re-  
105 coupling efforts that will incorporate additional functional components under a redesigned,  
106 sustainable coupling framework. It also helps us better understand how both models have  
107 evolved since their original coupling in 2005, thereby informing the development of a next-  
108 generation framework. In recognition of the increasing number of LSMs being coupled with  
109 ParFlow, we further propose a ParFlow-Land Surface Coupled Model Intercomparison Project  
110 (PLCMIP) to promote collaboration and knowledge exchange across the community.

111 **2. A brief review of ParFlow-Land/Atmosphere coupled modeling**

112 The coupled model provides a more realistic representation of groundwater dynamics than  
113 traditional LSMs, while also offering more advanced ecohydrological processes at the land  
114 surface than conventional groundwater models. Over the past two decades, its major scientific  
115 contributions can be summarized in three key areas:

116 (1) It captures the feedbacks from groundwater to land and atmospheric processes—an  
117 area often overlooked or omitted in both atmospheric and groundwater research  
118 communities.

119 (2) It highlights the critical range of water table depth (WTD) that mediates these feedbacks.

120 (3) It elucidates the impacts of land cover and climate change on groundwater and other  
121 complex ecohydrological interactions.

122 Because this manuscript is designed to synthesize the past, present, and future of the  
123 ParFlow-based coupled systems at this twenty-year juncture, this review primarily synthesizes  
124 advances within the ParFlow–LSM and ParFlow–atmosphere modeling family, while also briefly  
125 situating other groundwater–land coupling efforts in a broader community context.

126 **2.1 Feedbacks from groundwater to land surface and atmosphere**

127 Adding groundwater representation in ESMs reshapes the spatiotemporal distribution of  
128 soil moisture, which in turn controls surface turbulent fluxes and the evolution of the  
129 atmospheric boundary layer (Forrester and Maxwell, 2020; Rihani et al., 2015). This is primarily  
130 due to the limited simulation depth in LSMs and the absence of lateral groundwater flow. The  
131 former limits drainage in ridge areas, resulting in insufficient water release and an  
132 overestimation of soil moisture; the latter suppresses groundwater convergence in valley areas,  
133 leading to underestimation of soil moisture there.

134 Generally, lateral groundwater flow enhances soil moisture in topographic lows,  
135 suppresses boundary layer development, and increases the evaporative fraction, thereby  
136 weakening land–atmosphere coupling and reducing near-surface temperatures (Forrester and  
137 Maxwell, 2020; Keune et al., 2016). These responses are further modulated by the subsurface  
138 hydraulic conductivities ( $K$ ), with more pronounced sensitivities to  $K$  under simplified  
139 groundwater parameterizations (Williams and Maxwell, 2011; Keune et al., 2016; Rihani et al.,  
140 2010). Notably, the impact of groundwater and subsurface properties on surface flux  
141 partitioning and boundary layer development tends to be most pronounced in the afternoon,  
142 when radiative forcing peaks and land–atmosphere interactions intensify (Rahman et al., 2015;  
143 Rihani et al., 2015; Forrester and Maxwell, 2020; Maxwell et al., 2007).

144 Forrester and Maxwell (2020) conducted WRF-based weather simulations over the  
145 mountainous regions of Colorado to investigate the impact of different lower boundary  
146 conditions, providing a detailed explanation of the processes mentioned above. The study

147 included a baseline scenario and several comparative scenarios, with particular emphasis on  
148 one that used PF-WRF to explicitly represent three-dimensional groundwater flow. In the  
149 baseline scenario, conventional WRF simulation was employed, with the subsurface depth of  
150 2 m, divided into four layers with thicknesses of 0.1, 0.3, 0.6, and 1 m from top to bottom. The  
151 bottom boundary used the native Noah model setting, which allows free drainage and further  
152 adjusts fluxes based on terrain. In the PF-WRF scenario, the subsurface depth was increased  
153 to 102 meters by adding a fifth layer of 100 m in thickness, with the bottom boundary set as  
154 impermeable. The Noah model and ParFlow were coupled through the top four layers, resulting  
155 in a coupling depth of 2 m.

156 Simulation results showed that, in the PF-WRF scenario, enhanced drainage over ridge  
157 areas reduced soil moisture, while lateral groundwater convergence increased soil moisture in  
158 valleys. Correspondingly, the boundary layer height also exhibited increases in ridge areas and  
159 decreases in valley areas. These changes in soil moisture and boundary layer height showed  
160 significant seasonal variations. Furthermore, the results revealed that microtopography induced  
161 highly heterogeneous local variations in soil moisture. This, in turn, weakened the clear  
162 elevation-dependent trend observed in the baseline scenario.

163 Additionally, in the baseline scenario, the coupling strength between evaporative fraction  
164 (EF, the ratio of latent heat to the sum of latent and sensible heat) and boundary layer height  
165 was weakened or even reversed in the PF-WRF scenario. That is, the significant negative  
166 correlation between EF and boundary layer height decreased or turned positive; this may be  
167 due to the temporal variations in EF caused by lateral flow. Moreover, the PF-WRF scenario  
168 with lateral flow showed stronger morning mountain breezes (upslope) and valley breezes  
169 (downslope), which may have enhanced mountain-valley circulation. Lateral groundwater flow  
170 also modulated low-level convection in river valleys, particularly increasing convective available  
171 potential energy (CAPE) in the afternoon, thereby perturbing regional precipitation.

172 Keune et al. (2016) conducted simulations over the European CORDEX region using the  
173 TerrSysMP modeling system (Shrestha et al., 2014), setting up two scenarios: one with fully  
174 three-dimensional groundwater flow (3D) and the other with one-dimensional free drainage  
175 (FD). Similarly, their results revealed that different representations of groundwater led to  
176 variations in CAPE, indicating influences on the evolution of atmospheric boundary layer and  
177 free troposphere. The 3D scenario weakened land–atmosphere coupling, thereby suppressing  
178 the occurrence of extreme weather events, which is consistent with the findings of Forrester  
179 and Maxwell (2020). More specifically, the simulated 2 m air temperature was generally lower  
180 in the 3D scenario than in the FD scenario, providing useful insights for simulating European  
181 heatwaves during the study period.

182 The study also showed that model differences were primarily located in areas with shallow  
183 water tables (depth < 5 m), which aligns with findings of Forrester and Maxwell (2020) that  
184 humidity, potential temperature, and vertical wind exhibit more pronounced differences in  
185 mountainous valley regions. In addition, the study revealed that variations in deep soil (depth >

186 3 m) hydraulic conductivities led to discrepancies in simulation results. The FD scenario was  
187 more sensitive to the choice of conductivity values, suggesting that simplified physical  
188 representations may further amplify the impact of parameter uncertainty.

189 Williams and Maxwell (2011), using coupled PF-WRF simulations, further explored the  
190 feedbacks of geological conditions on land–atmosphere processes such as latent heat flux and  
191 wind speed. Based on idealized scenarios, they conducted ensemble simulations by perturbing  
192 the hydraulic conductivity field. The results showed that conditioning the hydraulic conductivity  
193 significantly reduced uncertainties in simulating land–atmosphere interactions compared to  
194 unconditioned cases. The ensemble mean was closer to the control scenario; for instance, the  
195 mean and distribution of simulated wind speed showed reduced uncertainty. These findings  
196 provide important implications for various wind energy applications.

197 Community-wide studies have also highlighted the importance of representing water-table  
198 dynamics within land-surface processes. Koirala et al. (2014) incorporated groundwater  
199 fluctuations into the MATSIRO land surface scheme and quantified the sensitivity of ET to  
200 capillary rise, showing that global mean ET increases by approximately 9% when water-table  
201 dynamics are included. Tian et al. (2012) further examined how hydraulic conductivities  
202 regulate ET by influencing both vertical and lateral groundwater fluxes, using a coupled  
203 AquiferFlow–SiB2 modeling framework. Using ParFlow-based coupled models, Tai et al. (2018)  
204 and Fang et al. (2022) demonstrated that explicitly resolving water-table dynamics helps explain  
205 mechanisms of plant mortality, while Abbaszadeh et al. (2025) reported improved simulations  
206 of land-surface fluxes when groundwater processes are represented. Miguez-Macho and Fan  
207 (2025) incorporated lateral surface-water and groundwater subsidies simulated by the ASAP  
208 model into a humidity index, providing a more accurate depiction of the timing and magnitude  
209 of water availability in hydrologically convergent lowlands. This enhancement better explains  
210 the monthly variations of leaf area index. A more recent study (Vogelbacher et al., 2025)  
211 extends beyond physically coupled modeling frameworks by showing that integrating water-  
212 table depth into a machine-learning system yields a more robust assessment of heatwave risks.

## 213 **2.2 The critical zone of WTD in groundwater–land interactions**

214 As discussed above, numerous studies have revealed feedbacks of groundwater on land–  
215 atmosphere processes. A key scientific question thus arises: what is the quantitative  
216 relationship between land surface states/fluxes and the WTD? Maxwell and Condon (2016), in  
217 their study over the continental US, confirmed the critical role of lateral groundwater flow in  
218 modulating the partitioning between evaporation (E) and transpiration (T). This influence is most  
219 pronounced when the WTD lies between 0.5 and 5 m. Shallower WTD leads to elevated bare-  
220 soil evaporation and transpiration, while deeper WTD suppresses both fluxes. Notably, in  
221 regions where bare-soil evaporation is limited and transpiration is sustained, the T/E ratio peaks.

222 Similarly, many studies using PF-CLM have identified a critical WTD range within which  
223 land surface variables—such as latent heat flux, sensible heat flux, and surface temperature—  
224 are highly sensitive to WTD but exhibit diminished sensitivity beyond this range (Figure 1). For

225 instance, Ferguson's work over the Little Washita watershed suggests a critical WTD range of  
226 approximately 1–10 m (Ferguson and Maxwell, 2012, 2011, 2010), while Yang et al. (2020);  
227 Yang et al. (2023) reported comparable results over the North China Plain. Rihani et al. (2015)  
228 also illustrate the coupling between WTD and planetary boundary layer depth in this transition  
229 zone from ridges to valleys along hillslopes. Fang et al. (2022) demonstrated a clear transition  
230 from hydraulic-failure-dominated mortality at shallow WTDs (<5 m) to carbon-starvation-  
231 dominated mortality under deep water-table conditions (>7.5–15 m). Generally, when WTD is  
232 shallower than this range, soil is nearly saturated and energy availability becomes the limiting  
233 factor, weakening the sensitivity of surface states/fluxes to WTD. Conversely, when WTD  
234 exceeds this range, gravity-driven drainage dominates, limiting moisture availability and again  
235 reducing sensitivity. The upper bound of this range is typically <1 m, while the lower bound  
236 often aligns with the model's coupling depth (Kollet and Maxwell, 2008). However, in some  
237 cases, such as Maxwell and Condon (2016), the lower bound extends beyond the nominal 2 m  
238 coupling depth, likely due to capillary rise from the water table.

239 This critical WTD range varies across regions, influenced by differences in subsurface  
240 characteristics and rooting depth, though current understanding remains limited. Fan et al.  
241 (2017), through analysis of over 2,200 global root depth observations and model-based  
242 inversion, showed that rooting depth is regulated by the capillary rise zone. Even within the  
243 same species and climate, rooting depth may vary with WTD conditions (Cannon, 1913). In  
244 some environments, vegetation develops both shallow fibrous roots and deep taproots to  
245 access water under varying conditions—shallow roots for near-surface moisture during wet  
246 periods, and deep roots for capillary water during droughts. On well-drained uplands, rooting  
247 depth is controlled by infiltration and may not reach significant depths (Sperry and Hacke, 2002;  
248 Schenk and Jackson, 2005; Xu and Li, 2008). In contrast, in shallow groundwater zones,  
249 oxygen stress may inhibit root growth and decouple vegetation from groundwater (Wagg, 1967;  
250 Follett et al., 1974; Martin, 1968; Armstrong et al., 1976). This adaptive rooting strategy  
251 suggests that in natural systems, the depth and intensity of groundwater–land surface coupling  
252 may exceed what models typically simulate.

253 Maxwell et al. (2007) further investigated how groundwater feedbacks on land surface  
254 processes change under different climate change scenarios, including hot, hot and dry, and hot  
255 and wet. It is not difficult to infer that changes in latent heat flux and recharge (precipitation  
256 minus ET) within the critical WTD range exhibit strongest spatial variability. Generally, these  
257 findings suggest that groundwater feedbacks on land surface processes are closely linked to  
258 topographic and climatic conditions. For instance, in the aforementioned mountainous regions  
259 of Colorado, spatial variability in WTD leads to diverse groundwater–land surface interactions.  
260 The transitional zones between ridges and valleys are often the key areas for such interactions.  
261 In humid regions, the water table often follows surface topography (Gleeson et al., 2011),  
262 facilitating strong groundwater–land surface coupling. However, in arid regions, WTD may  
263 exceed the lower bound of the critical range, reducing the significance of groundwater

264 feedbacks. In natural systems, this interaction is often governed by the complex interplay  
265 between climate, topography, geology, and vegetation.

### 266 **2.3 The impacts of land cover and climate changes on groundwater**

267 Climate change has exacerbated mountain pine beetle infestations, leading to widespread  
268 tree mortality in the Rocky Mountains (Bearup et al., 2014). Mikkelsen et al. (2013) studied the  
269 impacts of beetle-induced forest dieback on water and energy balances at the hillslope scale  
270 using PF-CLM simulations. An idealized hillslope model (500 m × 1000 m × 12.5 m) was used,  
271 with scenarios representing different stages of infestation—green, red, grey, and dieback—by  
272 modifying the leaf area index and stomatal conductance. Simulation results showed similar  
273 levels of ET across all scenarios in winter, but significantly higher ET in summer under the  
274 green scenario, primarily due to transpiration. In contrast, the other scenarios exhibited lower  
275 ET limited by soil moisture availability, with evaporation being the dominant process. The  
276 dieback scenario produced the highest peak in snow water equivalent (SWE), and reduced  
277 canopy cover allowed more solar radiation to penetrate, accelerating snowmelt. This earlier  
278 and more rapid melt resulted in earlier and higher streamflow peaks, as well as increased  
279 subsurface storage. A related particle tracking study (Bearup et al., 2016) further demonstrated  
280 greater groundwater contributions to streamflow during late summer.

281 Condon et al. (2020) conducted a continental-scale simulation across the United States  
282 using the PF-CLM CONUS 1.0 model (Maxwell et al., 2015) to examine groundwater responses  
283 to 1°C, 2°C, and 4°C warming scenarios. Warming was found to enhance ET, with shallow  
284 groundwater providing supplementary moisture to meet the increased demand, thereby  
285 partially mitigating land surface water stress. However, prolonged warming ultimately led to  
286 continuous groundwater depletion and a decoupling of groundwater from land surface  
287 processes. The magnitude of ET increases, and groundwater storage loss varied with WTD,  
288 with the strongest responses occurring within the previously identified critical WTD range.  
289 Overall, the humid eastern U.S. exhibited greater sensitivity to warming than the arid western  
290 regions. These findings highlight the risk of underestimating groundwater–land surface  
291 feedbacks when using simplified groundwater parameterizations in ESMs.

### 292 **2.4 Enhanced LSM functionality motivates recoupling**

293 These selected representative studies have demonstrated the critical role of groundwater  
294 in Earth system processes. Over the past two decades, CoLM—like many other LSMs—has  
295 undergone substantial development, including functional extensions, improved  
296 parameterization schemes, and the introduction of multiple alternative process representations.  
297 However, our understanding of how groundwater interacts with these additional processes—  
298 including how various parameterizations respond to and influence groundwater dynamics—  
299 remains limited. These limitations underscore the pressing need to upgrade the coupling  
300 between ParFlow and LSMs. The key scientific advances of CoLM are summarized as follows  
301 (Yuan and Dai, 2025):

302       **(1) Radiation transfer:** a three-dimensional vegetation shortwave (Yuan et al., 2014) and  
303 longwave radiation transfer scheme has been incorporated, the SNICAR snow radiation  
304 transfer scheme has been added to simulate snow albedo and radiation absorption within the  
305 snowpack, and an improved two-stream approximation scheme for vegetation radiation transfer  
306 has been provided (Yuan et al., 2017). **(2) Turbulent fluxes:** the model enhances the continuity  
307 of dynamic parameters and processes across transitions from dense to sparse vegetation.  
308 Resistance coefficients below the canopy are calculated using a profile integration method. A  
309 new turbulent exchange scheme supports multiple coexisting plant functional types (PFTs)  
310 within a three-dimensional canopy. Several soil resistance parameterizations are provided to  
311 improve surface evapotranspiration estimates. Additionally, a surface turbulent flux scheme has  
312 been introduced to account for large-eddy effects. **(3) Canopy interception and plant**  
313 **hydraulics:** the model includes multiple canopy interception schemes and a plant hydraulics  
314 module governed by Darcy's law. Different parameterizations emphasize distinct physical  
315 processes and support investigation of the evolution, drivers, and trends of interception under  
316 varying conditions. The hydraulics module replaces empirical formulations that relate plant  
317 stress to soil water potential and improves the simulation of land-atmosphere water exchange  
318 under changing environments. **(4) Leaf temperature:** A simplified one-dimensional two-big-  
319 leaf scheme has been implemented to improve the numerical stability of leaf temperature  
320 simulations. In addition, a new parameterization has been developed for leaf temperature in  
321 multi-PFT scenarios with a three-dimensional canopy structure. **(5) Other functional**  
322 **extensions:** additional modules have been developed for biogeochemistry, urban systems,  
323 crop modeling, land use and land cover change, wildfire, ozone-related ecophysiological stress,  
324 and integrated hydrological processes.

### 325 **3. Foundational step toward sustainable coupling**

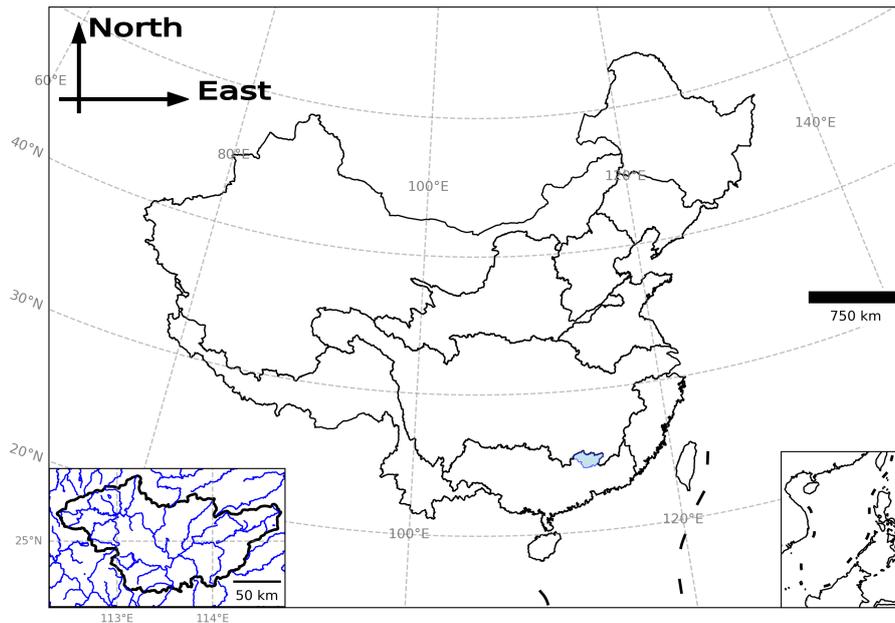
326       To explore the feasibility of re-coupling the latest versions of ParFlow and CoLM, we  
327 conducted a preliminary integration of the two models. This effort focuses exclusively on the  
328 basic water and energy modules of CoLM and is built upon the existing ParFlow-CLM coupling  
329 interface. That means that canopy interception, snow processes, and the surface energy  
330 balance (radiation, sensible and latent heat fluxes, and ground heat flux) were enabled in the  
331 current tests, whereas other functional extensions were kept inactive. Our goal is to understand  
332 how both models have advanced over the past two decades, in terms of functionality, code  
333 architecture (e.g., parallelism), data structures, I/O interfaces, and pre-/post-processing tools.  
334 This process also helps identify key variables and processes—along with their implementation  
335 in code—that are critical for a more comprehensive coupling effort. Although this re-coupling  
336 effort uses CoLM as an example, the experience and insights gained are also applicable to  
337 coupling ParFlow with other LSMs.

338       This initial re-coupling serves to evaluate model performance with respect to physical  
339 processes, particularly highlighting potential improvements gained through two decades of  
340 development. It also establishes a set of benchmarks for testing and debugging as more CoLM

341 modules are progressively incorporated. Without this incremental approach, the complexity of  
342 multiple physical processes would make testing and debugging considerably challenging. In  
343 addition, we fully leverage the lessons learned through trial and error over the past twenty years  
344 to ensure a more stable execution of the coupled model (Ferguson et al., 2016). While this  
345 phase emphasizes gaining a deeper understanding of the physical processes, future work on  
346 sustainable coupling will likely shift toward technical aspects—such as refining the coupling  
347 interface, improving modularity, and ensuring long-term maintainability. These efforts will  
348 collectively inform our understanding of the challenges and opportunities involved in  
349 establishing a sustainable coupling framework.

### 350 **3.1 Model setup, experimental design, and evaluation data**

351 The modeling domain, selected from the CONCN domain (Yang et al., 2025), is located in  
352 the North Pearl River Basin (Figure 2). This area was chosen as it serves as a demonstration  
353 area for the CONCN model and possesses more complete infrastructure e.g., the processed  
354 ERA5-Land reanalysis data (Muñoz-Sabater et al., 2021). To link the study domain with the  
355 coupled modeling framework, we next describe the model’s vertical and horizontal  
356 discretization. Since the CONCN model and CoLM use four and ten soil layers, respectively,  
357 the CONCN model structure was adjusted to align with CoLM’s vertical discretization. The  
358 ParFlow model employed in this study comprises 11 layers: the top 10 layers match CoLM in  
359 thickness, while the additional 11th layer represents the deep aquifer. ParFlow and CoLM are  
360 coupled through the top 10 layers. The coupled model maintains a horizontal resolution of ~1  
361 km, consistent with the CONCN model and includes 252 and 146 grid cells in the *x* and *y*  
362 directions, respectively. This corresponds to a spatial extent of approximately 242.35 km (*x*  
363 *direction*) × 140.41 km (*y direction*) × 103.43 m (*z direction*). Soil properties for CoLM inputs  
364 were derived from the Global Soil Dataset for Earth System Modeling (GSDE) (Shangguan et  
365 al., 2014). Soil parameters for ParFlow were reconstructed based on the sand and clay weight  
366 percentages from the same GSDE dataset, following the USDA soil classification system.  
367 Properties for the 11th layer were obtained from GLHYMPS 1.0 (Gleeson et al., 2011; Gleeson  
368 et al., 2014), as used in the CONCN model. The *e*-folding of aquifer hydraulic conductivity with  
369 depth was implemented using a characteristic depth of 50 m (Fan et al., 2007). Other surface  
370 input parameters—including Manning’s roughness coefficients, topographic slopes, and land  
371 cover types—were adopted directly from the CONCN model configuration (Yang et al., 2025).

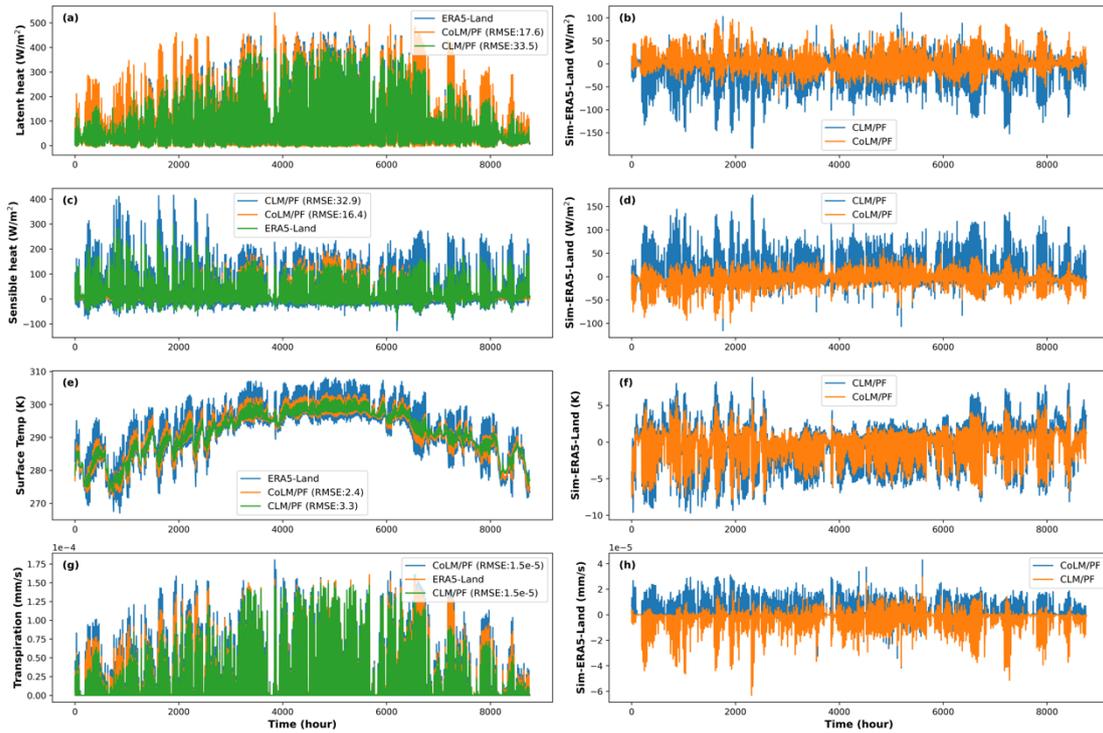


**Figure 2. Location of the modeling domain**

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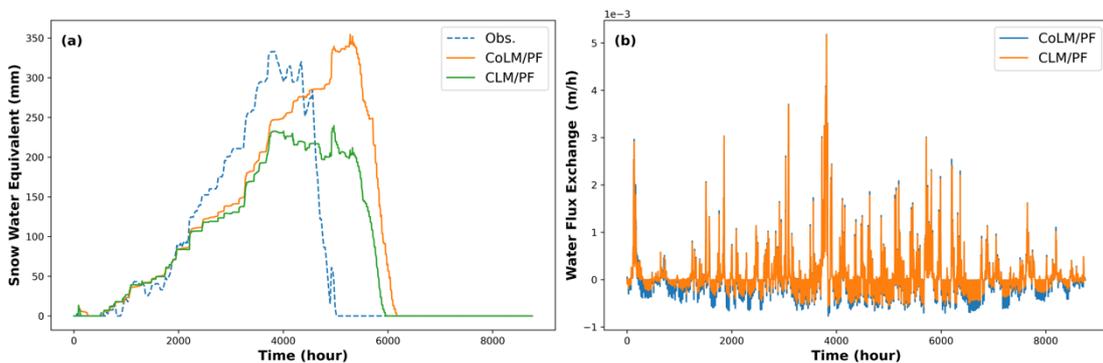
374 We first spun up the standalone ParFlow model using potential recharge data clipped from  
 375 the CONCN domain. Then we drove the coupled model using the 2018 meteorological forcing  
 376 from ERA5-Land reanalysis. Year 2018 was selected to keep consistency with the evaluation  
 377 year of the CONCN model. However, this is an area with limited snow. To demonstrate snow  
 378 performance, we created a synthetic case by applying the water year 2003 forcing from a  
 379 station (Defnet et al., 2024) located in Colorado to a single column model. To evaluate changes  
 380 in model performance, we also constructed 11-layer models (with 10 coupled layers) using the  
 381 old ParFlow-CLM for both real-world and synthetic cases. For the real-world case, we  
 382 compared the simulated sensible heat, latent heat, skin temperature, transpiration, SWE, and  
 383 the water flux exchange between the new and old models (Figures 3 and 4). Here, water flux  
 384 exchange refers to the source/sink terms in Richards' equation: positive values represent  
 385 infiltration, while negative values are caused by ET. We also evaluated the simulation  
 386 performance of the first four variables using ERA5-Land reanalysis. For the synthetic cases,  
 387 we used data from the Snow Telemetry (SNOTEL) network maintained by the Natural  
 388 Resources Conservation Service (NRCS)—specifically, the measured SWE at the same  
 389 location as the meteorological forcing—to evaluate the models' overall ability to simulate the  
 390 timing and magnitude of snowpack.

391



392  
 393 **Figure 3. Comparison of latent heat flux, sensible heat flux, surface temperature, and**  
 394 **transpiration between the old CLM/ParFlow and the new CoLM/ParFlow models. The**  
 395 **corresponding values from ERA5-Land are plotted in the left column for reference. The**  
 396 **right column shows the differences between the model simulations and ERA5-Land for**  
 397 **each variable. Each subplot represents spatial averages over the entire modeling**  
 398 **domain. For clarity and to prevent overlapping, the plotting order is intentionally varied**  
 399 **across subplots.**

400

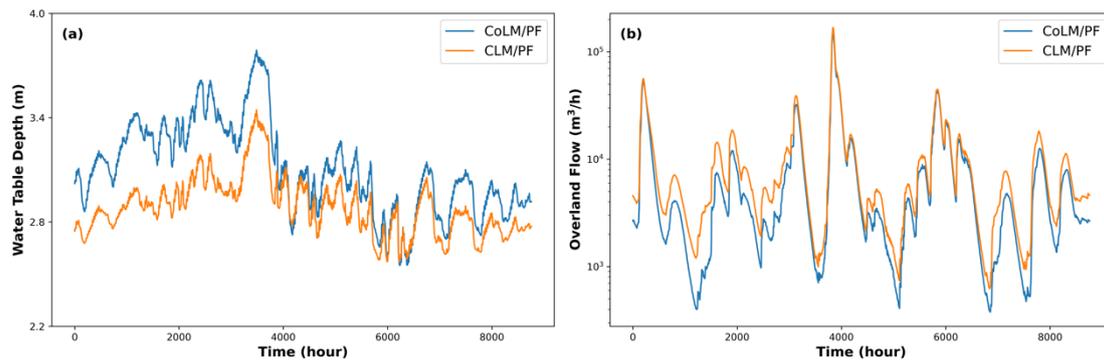


401  
 402 **Figure 4. (a) shows the simulated snow water equivalent from the CoLM/ParFlow and**  
 403 **CLM/ParFlow single column models, compared against SNOTEL observations. (b)**  
 404 **presents the spatially averaged net water fluxes from CoLM and CLM to ParFlow,**  
 405 **representing the source and sink terms in the ParFlow domain; both fluxes represent**  
 406 **spatial averages over the entire modeling domain.**

407 **3.2 Performance gains from updated CoLM support recoupling**

408 Simulations of all variables by CoLM/PF exhibit improved performance relative to CLM/PF  
 409 when evaluated against ERA5-Land reanalysis data (Figure 3). CoLM/PF produces a more  
 410 realistic partitioning of turbulent fluxes, characterized by increased latent heat and reduced  
 411 sensible heat (Figures 3a and 3c). Notably, transpiration simulated by CoLM/PF is substantially  
 412 higher and aligns more closely with ERA5-Land data (Figure 3g). Additionally, CoLM/PF more

413 accurately reproduces the fluctuations in land surface temperature compared to CLM/PF  
 414 (Figure 3e). In the single column simulations (Figure 4a), CoLM/PF also generates a higher  
 415 peak SWE than CLM/PF, showing better agreement with SNOTEL observations, although both  
 416 models display deviations in the timing of SWE accumulation. This discrepancy may stem from  
 417 the idealized subsurface configurations used in both models. Improvements in both  
 418 transpiration and SWE are further supported by previous research; for instance, O'Neill et al.  
 419 (2021) reported consistently lower ET and SWE from CLM/PF in the assessment of CONUS  
 420 1.0 model. The overall advancement in model performance can likely be attributed to the more  
 421 sophisticated process representations embedded in CoLM.



422  
 423 **Figure 5. (a) and (b) show the simulated water table depth and overland flow by**  
 424 **CoLM/ParFlow and CLM/ParFlow, respectively. Each subplot represents spatial**  
 425 **averages over the entire modeling domain.**

426 Figure 4b illustrates the net fluxes transferred from the land surface to the subsurface,  
 427 which directly influence hydrologic dynamics such as WTD and overland flow. These exchange  
 428 fluxes show greater variability in the CoLM/PF simulation, suggesting more dynamic surface–  
 429 subsurface interactions. Consistent with this, Figure 5 reveals more pronounced temporal  
 430 variability in both WTD and overland flow. A generally deeper water table is observed in  
 431 CoLM/PF (Figure 5a), which is likely a result of the higher plant water uptake, i.e., increased  
 432 transpiration, depicted in Figures 3a, 3g and 4b. Consequently, the reduction in baseflow from  
 433 groundwater may explain the observed decrease in low levels of overland flow (Figure 5b).

434 To improve the representation of turbulent exchanges between the vegetation canopy and  
 435 the atmosphere, the model employs a profile-integrated approach to resolve key dynamical  
 436 parameters (e.g., turbulent diffusivity  $K(z)$ ) with explicit vertical resolution (Dai et al., 2019b). In  
 437 particular, resistance-related variables—such as displacement height ( $d$ ) and roughness length  
 438 ( $z_0$ ), which characterize canopy-atmosphere momentum exchange, as well as aerodynamic  
 439 resistances for leaves ( $r_b$ ) and ground surface ( $r_d$ ), which govern within-canopy and near-  
 440 surface heat and vapor transfer—are refined to account for structural heterogeneity (Dai et al.,  
 441 2019b). Meanwhile, profile-integrated functions are dynamically computed based on vegetation  
 442 structure and atmospheric stability, and directly determine resistance terms (e.g.,  $r_{ah}$ ,  $r_{aw}$ ) (Yuan  
 443 and Dai, 2025). This also includes revised roughness length formulations that explicitly account  
 444 for atmospheric stability (Yuan and Dai, 2025), extending beyond the original neutral-based  
 445 assumptions in schemes such as Raupach (1994, 1992). This combined approach yields a

446 more physically consistent and vertically continuous treatment of turbulent fluxes under non-  
447 neutral stratification, enhancing realism in complex canopy conditions.

448 In addition, other schemes—such as those related to soil thermal parameters (including  
449 heat capacity and heat conductivity), as well as soil color and associated reflectance—also  
450 differ between the CoLM/PF and CLM/PF models (Yuan and Dai, 2025). All of these differences  
451 motivate a coupled model intercomparison project to evaluate how different schemes, either  
452 within a single model or across different models, affect the performance of the coupled model  
453 and land–hydrology process interactions. Since 2005, ParFlow has also undergone several  
454 major developments that significantly affect model performance (Kuffour et al., 2020), such as  
455 the integration of overland flow (Kollet and Maxwell, 2006) and the implementation of the  
456 terrain-following grid (Maxwell, 2013). Both test cases in this study already used these modern  
457 capabilities. Features such as GPU acceleration (Hokkanen et al., 2021) and reservoir  
458 capabilities (West et al., 2025) in ParFlow exist, but they are not relevant to the test cases here.

459 In this initial coupling process, we found that the main changes in CoLM were related to  
460 data structure, module organization, module names, and variable naming conventions. For  
461 example, structures were broken down into multiple arrays, modules were split and reorganized  
462 based on functionality, some modules were removed from the main program and used as  
463 preprocessing components, and module adjustments were often accompanied by renaming. A  
464 large number of variable names were also changed. Moreover, the inclusion of multiple  
465 parameterization schemes has increased code complexity to some extent, resulting in  
466 significantly larger module sizes. Nevertheless, most physical processes have retained their  
467 original core parameterizations. This means that the primary task in this initial coupling stage  
468 is to identify the key physical processes and the critical variables within the new system  
469 structure. Several new parameterization schemes have also been implemented—for example,  
470 those associated with the turbulent exchange discussed above—though the application of other  
471 schemes will require further testing in future work.

#### 472 **4. A sustainable recoupling framework for future development**

473 Here, we propose a sustainable framework for future CoLM/ParFlow coupling based on  
474 our preliminary work (Figure 6). This framework consists of four key components: a coupler-  
475 based architecture, a robust initial foundation, protocols for scalable upgrades, and a  
476 community interaction platform. The four components play different roles. The first two—  
477 coupler-based architecture and early-stage grid/process mapping—form the structural  
478 foundation that determines long-term sustainability. They address issues that cannot be solved  
479 through implementation refinements alone, such as maintaining independent model evolution  
480 and enabling robust cross-grid exchanges. The latter two components—developer protocols  
481 and community interaction—further enhance maintainability and extensibility once the  
482 structural basis is in place. These collaborative conventions support scalable development but  
483 cannot replace the structural requirements themselves, nor can they reduce the inherent

484 complexity of multi-model coupling. Effective participation still requires sufficient domain  
485 knowledge and technical expertise.

486       • **Coupler-based architecture for long-term sustainability**

487       While the current ParFlow-Land interface built in ParFlow supports efficient coupling with  
488 land surface and atmospheric models, demonstrates good parallel performance, and avoids  
489 the overhead associated with inter-model communication, it lacks compatibility with  
490 standardized coupling frameworks and protocols. This limits the integration of coupled models  
491 into broader Earth system modeling frameworks. In contrast, coupler-based architectures—  
492 such as ESMF/NUOPC, CESM/cpl7, and OASIS3-MCT—are now standard in modern Earth  
493 system modeling. They preserve the native data structures, domain decomposition, and parallel  
494 logic of each model, which is particularly important given the substantial structural differences  
495 between ParFlow and CoLM. For instance, this approach allows retaining ParFlow's GPU-  
496 based parallelism (Hokkanen et al., 2021) and CoLM's MPI-based structure, along with their  
497 respective domain decomposition strategies. It also enables continued use of each model's  
498 preferred data format and processing tools—for example, ParFlow's `.pfb` format and `pfttools`,  
499 as well as CoLM's NetCDF-based workflow. Adopting a standardized coupler thus facilitates  
500 modular development, cross-system compatibility, and long-term maintainability. Looking  
501 forward, such coupler-based designs could also be extended to support surrogate model  
502 integration (Bennett et al., 2024; Tran et al., 2021), enabling hybrid workflows that combine  
503 physical models and AI-based components.

504       • **Strong foundations through early-stage mapping**

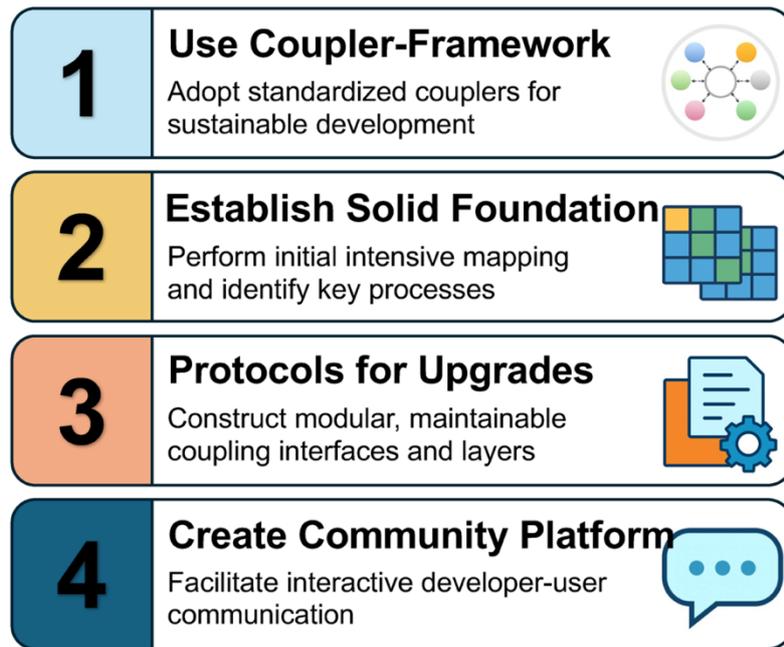
505       Laying a solid foundation during the initial coupling phase is critical. First, a mapping  
506 between ParFlow's grid and CoLM's subgrids must be established to support future model  
507 extensions. The current coupling only supports integration based on the LCT (Land Cover Type)  
508 subgrid, whereas important functional extensions such as biogeochemistry and 3D vegetation  
509 canopy processes rely on plant function types (PFTs) and the associated PFT and PC (Plant  
510 Community) subgrids. The mapping between grids of different models is a key concern in the  
511 coupling community and directly affects coupling performance (Valcke, 2022). Currently, most  
512 approaches rely on physical interpolation methods; incorporating an AI-based scale  
513 transformation layer with mass conservation constraints could be a promising enhancement.  
514 Second, key variables and processes from newly introduced modules or previously untested  
515 parameterizations must be identified. For example, the plant hydraulics module requires soil  
516 hydraulic conductivity fields, which are not included in the current coupling interface. More  
517 importantly, a structured logging system should be implemented to track all exchanged  
518 variables, their associated modules, and the corresponding grid structures, thereby ensuring  
519 transparency and traceability throughout development. This logging mechanism differs from  
520 conventional version-control systems in that it records the evolution of coupling-relevant  
521 variables and grid mappings rather than general code revisions, providing scientific rather than  
522 software-level traceability.

523       • **Protocols for efficient and maintainable coupler upgrades**

524       Two key aspects are emphasized. First, the architecture of interfaces and coupling layers  
525 should be designed for long-term clarity and ease of maintenance. Taking ESMF/NUOPC as  
526 an example, the model-side interfaces and coupler-side connector and mediator layers are  
527 implemented with a focus on modular organization, encapsulated data exchange, and well-  
528 structured control flow, ensuring that the system can be reliably extended as new model  
529 features or physical processes are introduced. For example, TerrSysMP achieves good  
530 modularity by separating tasks such as sending/receiving fields, grid mapping, and variable  
531 registration into dedicated files (Shrestha et al., 2014). TerrSysMP2 further improves on this  
532 design by organizing these components within a single Fortran module, which makes the  
533 interface structure clearer and simplifies the CMake build process (Poll et al., 2024). Second,  
534 developers introducing new modules, parallelization strategies, or grid structures, within one  
535 model must explicitly assess their potential impact on the other model, clarify any newly  
536 introduced variables or data structures to be exchanged via the coupler, and submit pull  
537 requests with corresponding explanations. Senior maintainers should review these changes  
538 and provide targeted feedback on necessary updates to the interface and coupling logic. All  
539 modifications affecting model interaction must be tracked in the logging system described  
540 above, and no update should be considered complete until it is formally registered in the log.

541       • **Community platform for collaboration and maintenance**

542       A dedicated community platform—such as a GitHub repository, mailing list, or model  
543 portal—should be established to support developer–user interaction, technical discussion, and  
544 feedback collection. This platform will also serve to announce new model releases, coupling  
545 layer updates, or changes in the logging system. Transparent communication and community-  
546 driven collaboration are essential for the long-term sustainability and extensibility of the coupled  
547 model system. Looking forward, we envision extending this platform into a broader, community-  
548 driven environment for managing and operating ParFlow–LSM coupled models, drawing  
549 inspiration from efforts such as eWaterCycle (Hut et al., 2022). Beyond supporting collaboration  
550 and information sharing, such a platform could streamline model configuration, coupled-model  
551 execution workflows, data processing/formatting, and reproducibility—thereby accelerating  
552 adoption, improving transparency, and fostering interoperability across hydrological and Earth  
553 system science communities. This would also address a current gap, as ParFlow-based  
554 coupled systems remain largely fragmented and lack standardized tools for interfacing with  
555 upstream/downstream models, verification and benchmarking, and public release to users.



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**Figure 6. The coupling framework for sustainable development**

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**5. ParFlow-Land coupled model intercomparison project (PLCMIP)**

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Over the past decades, numerous land and/or atmosphere models coupled with ParFlow have been developed (Table 1). These models vary in their functional capabilities and adopt different coupling strategies, which may significantly affect computational efficiency. The two models coupled with CoLM aim to understand the fundamental interactions of water and energy between subsurface and land surface processes (Dai et al., 2003; Maxwell and Miller, 2005). In contrast, the two models coupled with ARPS and WRF (Maxwell et al., 2007; Maxwell et al., 2011; Skamarock and Klemp, 2008; Xue et al., 2000; Xue et al., 2001), along with the two generations of TerrSysMP (Shrestha et al., 2014; Oleson et al., 2008; Lawrence et al., 2019; Poll et al., 2024), provide capabilities to explore two-way feedbacks across each interface within the subsurface–land surface–atmosphere system. Furthermore, the coupling of ParFlow with TREES (Tai et al., 2018; Mackay et al., 2015), ELM-FATES (Fang et al., 2022; Caldwell et al., 2019; Fisher et al., 2015; Leung et al., 2020), and LPJ-GUESS (Jia et al., 2025) introduces advanced vegetation dynamics into land surface process representations. Finally, integration with NASA-LIS enables data assimilation within the coupled modeling framework (Maina et al., 2025; Kumar et al., 2008; Niu et al., 2011; Abbaszadeh et al., 2025), and TerrSysMP also incorporates the PDAF (Parallel Data Assimilation Framework) to support data assimilation capabilities (Kurtz et al., 2016). Overall, most of the ParFlow-based coupled systems are implemented through modular integration–embedding one model within another–whereas TSMP and ParFlow-LIS represent coupler-based architectures that mediate data exchange among components.

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Model intercomparison provides a valuable means to assess model development and foster connections or collaborations across research communities. Several well-known

581 intercomparison projects exist, such as the Coupled Model Intercomparison Project (CMIP) for  
582 ESM intercomparison (Eyring et al., 2016), and the Land Surface, Snow and Soil Moisture  
583 Model Intercomparison Project (LS3MIP) (Van Den Hurk et al., 2016), which is designed to  
584 assess the performance of land modules in current ESMs. In addition, individual  
585 intercomparison activities have also been widely conducted within the land surface modeling  
586 community (Scanlon et al., 2018; Liu et al., 2023). ParFlow has also participated in various  
587 model intercomparison projects involving hydrologic models and an increasing number of  
588 individual modeling studies, such as those by Maxwell et al. (2014); Sulis et al. (2017); Kollet  
589 et al. (2017); Sulis et al. (2010). Given the differences among the ParFlow-based coupled  
590 models mentioned above, a dedicated model intercomparison project (MIP) is needed to  
591 systematically evaluate coupled models and support the development of a community platform  
592 for benchmarking and collaboration, with the following objectives:

- 593 • To quantify the strength and spatiotemporal variability of groundwater–land–  
594 atmosphere interactions resulting from different parameterization schemes used in  
595 various land surface and atmospheric models.
- 596 • To evaluate the parameter sensitivity of each scheme, ensuring that differences  
597 attributed to model structure are not confounded with parameter choices.
- 598 • To compare computational efficiency across different coupling strategies.
- 599 • To identify the unique functionalities and strengths of each coupled model, providing  
600 users with guidance in selecting the most appropriate model for their specific research  
601 needs.

602 To ensure meaningful and comparable evaluations across models, the PLCMIP will  
603 encourage the use of standardized benchmark cases—either synthetic experiments or a  
604 common real-world watershed—as well as unified datasets for parameters and meteorological  
605 forcing. In addition, other groundwater-land coupled models, as well as land surface models  
606 with improved groundwater parameterizations, are likewise encouraged to participate in this  
607 intercomparison effort. Representative examples include Shen et al. (2016); Zeng et al. (2018);  
608 Tian et al. (2012); Niu et al. (2014); Sutanudjaja et al. (2014); Liao et al. (2025); Miguez-Macho  
609 and Fan (2025); Akhter et al. (2025); Dai et al. (2019a), although participation in PLCMIP is not  
610 limited to these.

## 611 **6. Summary**

612 Twenty years after the original ParFlow-CLM coupling (Maxwell and Miller, 2005), this study  
613 reaffirms the long-term scientific and technical significance of that foundational effort. Over two  
614 decades, the coupled system has made major contributions in establishing the critical role of  
615 groundwater in modulating subsurface–land–atmosphere feedbacks and identifying the  
616 existence of a critical water table depth range that governs these bidirectional interactions.  
617 Technically, this coupling demonstrated a viable approach for integrating a groundwater model  
618 with a land surface scheme—the lower boundary of Earth system models—thereby providing  
619 a template for incorporating groundwater processes into ESMs. To revisit and update this

620 legacy, we carried out a preliminary re-coupling of the latest versions of ParFlow and CoLM,  
621 focusing on core water and energy processes. This re-coupling already reveals improved model  
622 performance and provides a functional platform for incremental expansion and benchmarking.

623 Looking ahead, several key steps are essential for advancing a sustainable and extensible  
624 ParFlow–LSM coupling framework. Achieving this vision will require a more comprehensive  
625 and community-oriented design. This includes adopting a lightweight coupler architecture that  
626 preserves each model’s native data structures, parallel strategies, and processing tools, while  
627 supporting modular integration of new physical or surrogate components. To ensure long-term  
628 maintainability and usability, we also envision a community platform that unifies model  
629 configuration, user workflows, and benchmarking functions. Such a platform would enhance  
630 transparency, reproducibility, and ease of adoption across the hydrologic and Earth system  
631 modeling communities. In parallel, we propose launching a model intercomparison project  
632 (PLCMIP) to systematically evaluate performance, compare coupling strategies, and guide  
633 future development.

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**Table 1. ParFlow and Land/Atmosphere coupled models**

<b>Coupled model</b>	<b>Model description</b>	<b>Coupling approach</b>	<b>Reference</b>
CoLM	The Common Land Model	CoLM as a subroutine	<b>Maxwell and Miller, 2005;</b> Dai et al., 2003
ARPS	The mesoscale atmospheric model Advanced Regional Prediction System; coupled with the built-in land surface model	ARPS as a subroutine	<b>Maxwell et al., 2007;</b> Xue et al., 2000, 2001
WRF	The community numerical weather prediction Weather Research and Forecasting model, version 3.0; coupled with the built-in Noah model	WRF as a subroutine	<b>Maxwell et al., 2011;</b> Skamarock and Klemp, 2008
CLM3.5	The NCAR Community Land Model (version 3.5) in TerrSysMP	<b>Coupler.</b> Ocean Atmosphere Sea Ice Soil, version 3.0 (OASIS3)	<b>Shrestha et al., 2014;</b> Oleson et al., 2008
TREES	A plant physiology model: Terrestrial Regional Ecosystem Exchange Simulator	TREES as a subroutine	<b>Tai et al., 2018;</b> Mackay et al., 2015
ELM	The Energy Exascale Earth System Model (E3SM) land model (ELM) that includes the Functionally Assembled Terrestrial Ecosystem Simulator (FATES)	ParFlow as a subroutine	<b>Fang et al., 2022;</b> Caldwell et al., 2019; Leung et al., 2020; Fisher et al., 2015
eCLM	An adaption of the NCAR Community Land Model (version 5.0) in TerrSysMP2	<b>Coupler.</b> OASIS3-MCT, where MCT represents Model Coupling Toolkit	<b>Poll et al., 2024;</b> Lawrence et al., 2019
Noah-MP	Noah-MP in the NASA Land Information System (LIS)	<b>Coupler.</b> The Earth System Modeling Framework and the National United Operational Prediction Capability (ESMF/NUOPC)	<b>Maina et al., 2025;</b> Abbaszadeh et al., 2025; Kumar et al., 2008; Niu et al., 2011
LPJ-GUESS	A process-based dynamic vegetation-terrestrial ecosystem model	<b>Coupler.</b> In-house developed	<b>Jia et al. (2025)</b>
CoLM2024	The Common Land Model, version 2024	CoLM2024 as a subroutine	<b>This study</b>

638 **Code and data availability**

639 The datasets used in this study are all from public sources and are cited in the main text.  
640 ParFlow version 3.13, as used in this study, is available at  
641 <https://doi.org/10.5281/zenodo.4816884> (Smith et al., 2024). The new ParFlow–CoLM model  
642 and the test cases, including input and output files, are available at  
643 <https://doi.org/10.5281/zenodo.16879407> (Yang, 2025), and a copy is also available on GitHub  
644 at <https://github.com/aureliayang/parflow-colm>.

645 **Author contributions**

646 Conceptualization: CY and RM. Methodology: CY, YD, and RM. Investigation: CY, AS, SZ,  
647 YD, SK, and RM. Resources: CY, YD, and RM. Writing (original draft): CY. Writing (review and  
648 editing): CY, YD, SK, and RM.

649 **Competing interests**

650 The contact author has declared that none of the authors has any competing interests.

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