Hydrology and Earth System Sciences

Notes on revision made to manuscript egusphere-2025-4623

Reviewer 1

Reviewer Comment 1.1 — I would like to compliment the authors on a very thorough and useful paper. I think there is great value in this very thorough review, and I think output such as Figure 6 can be very helpful. I did find the paper very dense which affects its readability; I have included some feedback below which maybe helps in addressing this.

Reply: We thank the reviewer for taking the time to read the manuscript and provide constructive feedback. In response to the comments, we have revised the paper to improve clarity and readability by adding a table of key definitions (Table 1), introducing a new subsection on the roles of the statistical/ML component in hybrid models (Section 4.2), and expanding the discussion of future directions, including links to socio-hydrological modeling (Section 5). Detailed responses to all comments are provided below.

Reviewer Comment 1.2 — There are a lot of different definitions discussed including their synonyms, and I wondered if adding a box with key definitions may help the reader. (eg two-way (or loosely) coupled models and tightly coupled models, etc.) Or maybe it can be added to existing figures such as figure 2.

Reply: As per your suggestion, we have added Table 1 with definitions for 11 technical terms.

Term	Definition
Compound flooding	Flooding arises from a combination of multiple drivers—such as storm surge, river discharge, rainfall, waves, or tides—whose interactions may amplify the hazard (Moftakhari et al., 2017; Wahl et al., 2015).
Process-based model	A numerical model that solves governing physical equations (e.g., Navier–Stokes, shallow-water equations) to simulate hydrodynamic, hydraulic, atmospheric, or surface-runoff processes.
Statistical model	A model that represents system behavior through probability distributions, empirical relationships, or data-driven statistical structures rather than directly solving physical equations.
Coupling	The integration of two or more models so that the output of one drives (and sometimes is also driven by) another, allowing different environmental domains to be represented in one workflow.
Two-way (loosely) coupled model	Two independent models run separately but exchange information in both directions at set intervals. The codes remain distinct and are called iteratively, so feedback is captured but with lower temporal granularity than in tight coupling (Santiago-Collazo et al., 2019).

Term	**Definition**
Tightly (fully) coupled model	Model components are merged into a single executable or solver framework and share state variables at every (or very fine) time-step, ensuring high-frequency, bidirectional feedback (Santiago-Collazo et al., 2019).
Bias correction	Statistical adjustment of model outputs to correct systematic deviations between modeled and observed data (Maraun and Widmann, 2018).
Data assimilation	Statistical methods that blend model forecasts with observations to estimate the evolving system state (Moradkhani et al., 2005).
Uncertainty quantification	Identification, characterization, and propagation of uncertainties arising from forcings, parameters, initial states, assumptions and model structure—and strategies to reduce them (Abbaszadeh et al., 2022; Muñoz et al., 2024).
Copula	A multivariate distribution that couples given marginals into a joint distribution, allowing flexible modelling of dependence (including tail behavior) (Nelsen, 2006).
Physics-informed machine learning	Machine-learning techniques in which physical laws (e.g., partial differential equations, conservation principles) are imposed as soft constraints in the loss function or as hard constraints that are built directly into the model architecture, yielding data-efficient, physically consistent surrogates (Raissi et al., 2019).

Reviewer Comment 1.3 — In sections 3.1 and 3.2, I was wondering about the "statistical component" and whether it would help to include a classification of the different roles or function of the statistical component within the different types of coupling. Clarifying the different roles of the statistical component within a hybrid model may help users to classify their specific hybrid approach?

Reply: In the revised version, we added a new section, "4.2 Roles of the statistical component in hybrid models," to summarize the different functions of the statistical component within a hybrid model:

"*4.2 Roles of the statistical component in hybrid models*

In hybrid modeling frameworks, the statistical/ML component plays different roles depending on the coupling strategy and the compound flood problem being addressed. Although Section 3 introduces statistical tools within each hybrid category, the functional purpose of the statistical block varies considerably across sequential, feedback, and ensemble designs. Across these paradigms, the statistical/ML block typically performs one or more of the five roles listed in Table 2:

Table 1. Roles of the statistical/ML component across hybrid modeling pathways

Role of statistical/ML component	Description	Sequential	Feedback	Ensemble
(1) Boundary/driver generator	Supplies synthetic or real-time forcings (e.g., rainfall, discharge, surge) as inputs to a physics-based solver.	✓	—	(✓)*
(2) Scenario sampler/event-catalogue builder	Draws joint extremes (e.g., via copulas/multivariate methods) to expand beyond historical records.	✓	(✓)*	(✓)*
(3) Physics surrogate	Provides a computationally efficient surrogate for an otherwise expensive physics-based model (e.g., rainfall–runoff, PIML hydrodynamics).	—	✓	(✓)*
(4) State updater	Assimilates observations or corrects model states during runtime; characteristic of two-way feedback systems.	—	✓	(✓)*
(5) Ensemble aggregator	Combines independent predictions using performance-, uncertainty-, or cost-based weighting.	—	—	✓

* Parentheses indicate roles that may appear in some implementations but are not core to the pathway.

Mapping these roles helps clarify how the statistical component contributes to the broader simulation framework and provides a consistent basis for classifying hybrid approaches. As summarized in Table 2, sequential hybrids typically rely on roles (1) and (2); feedback hybrids make use of roles (3) and (4) (and occasionally role 2); and ensemble hybrids center on role (5) while potentially incorporating roles (1)–(4) within individual ensemble members. This functional perspective highlights that the statistical or ML component is not a single construct but a spectrum of tasks that complement the physics engine in different ways."

Reviewer Comment 1.4 — Finally, I was wondering if there would be premise in adding a small discussion about linking (the framework of) compound flood modelling to more socio-hydrological models that capture not only compound flood / hydrological dynamics but also their interactions with people; eg https://gmd.copernicus.org/articles/16/2437/2023/?.

Reply: We added a new paragraph to Section 5 to emphasize this potential future pathway:

"*Emerging socio-hydrological and agent-based frameworks also offer opportunities for expanding compound flood modeling beyond physical drivers alone. These models explicitly simulate the feedbacks between human decisions and hydrological responses across a wide range of spatial scales, from large-scale agent-based systems, where millions of agents interact dynamically with soil moisture, groundwater, reservoirs, and routing processes (De Bruijn et al., 2023), to household-*

level adaptation models (Haer et al., 2020), catchment-scale frameworks that couple agent behavior with calibrated runoff responses (Sousa et al., 2025), behavior-aware reservoir-operation schemes (Gautam et al., 2025), and more generic socio-hydrological agent-based platforms developed for integrated water management applications (Lillo-Saavedra et al., 2024). Integrating compound flood frameworks with such socio-hydrological models could allow future studies to capture not only the multivariate flood physics but also how human behavior, adaptation, exposure, and decision-making co-evolve with compound flood hazards under changing climate and socioeconomic conditions."

References:

De Bruijn, J. A., Smilovic, M., Burek, P., Guillaumot, L., Wada, Y., & Aerts, J. C. (2023). GEB v0. 1: a large-scale agent-based socio-hydrological model–simulating 10 million individual farming households in a fully distributed hydrological model. *Geoscientific Model Development*, *16*(9), 2437-2454.

Haer, T., Husby, T. G., Botzen, W. W., & Aerts, J. C. (2020). The safe development paradox: An agent-based model for flood risk under climate change in the European Union. *Global Environmental Change*, *60*, 102009.

Gautam, S., Park, S., Yu, D. J., Garcia, M., Sivapalan, M., & Shin, H. C. (2025). Homo juridicus, homo heuristicus, and homo anticipans: A sociohydrological study of operator behavior and flood-drought tradeoffs in reservoirs. *Water Resources Research*, *61*(11), e2024WR039447.

Lillo-Saavedra, M., Velásquez-Cisterna, P., García-Pedrero, Á., Salgado-Vargas, M., Rivera, D., Cisterna-Roa, V., ... & Gonzalo-Martín, C. (2024). Socio-Hydrological Agent-Based Modeling as a Framework for Analyzing Conflicts Within Water User Organizations. *Water*, *16*(22), 3321.

Sousa, D. S., Silva, E. P., de MA Alves, C., Minoti, R. T., & Vergara, F. E. (2025). Coupling data-driven agent-based and hydrological modelling to explore the effect of collective water allocation strategies in environmental flows. *Journal of Hydrology*, *652*, 132670.

Reviewer Comment 1.5 — Some literature suggestions. Tilloy et al 2019, Mishra et al 2022.

Reply: As per your suggestion, we cited these two papers in the Introduction:

- Tilloy, A., Malamud, B. D., Winter, H., & Joly-Laugel, A. (2019). A review of quantification methodologies for multi-hazard interrelationships. *Earth-Science Reviews*, *196*, 102881.

- Mishra, A., Mukherjee, S., Merz, B., Singh, V. P., Wright, D. B., Villarini, G., ... & Stedinger, J. R. (2022). An overview of flood concepts, challenges, and future directions. *Journal of hydrologic engineering*, *27*(6), 03122001.