Dear Dr. Yi He,

I would like to express my sincere gratitude for the insightful and constructive feedback you provided on our manuscript. Your comments have been incredibly helpful in improving the clarity and quality of our work, and we truly appreciate the time and effort you dedicated to reviewing it. All the comments have been considered and a point-by-point response has been provided below.

The point-by-point response is formatted as follows:

- Your comments are shown in blue
- Our responses are shown in black
- The changes in the manuscript are shown in red. The line numbers indicated in this response are those in the "Revised Manuscript with no changes marked" document
- The unchanged parts of the manuscript are shown in black

1. In your revised manuscript, you state "the Xin'anjiang model is only suitable for humid and semi-humid regions where the saturation-excess runoff mechanism is dominant and is not applicable to arid and semiarid regions." It is not necessarily true that saturation-excess runoff mechanism is not present in some semiarid regions. This is still debatable, and it would be better to say "the Xin'anjiang model is mostly suitable for humid and semi-humid regions where the saturation-excess runoff mechanism is dominant and is less or not applicable to arid and semiarid regions."

Response: Thank you for your helpful suggestion. We have rewritten the sentence as per your advice to avoid any potential controversy (<u>Lines 667-669</u>).

Revised Manuscript LINES 667-669:

Therefore, the Xin'anjiang model is mostly suitable for humid and semi-humid regions where the saturation-excess runoff mechanism is dominant and is less or not applicable to arid and semiarid regions.

2. "As long as the warming-up period is adequately long", this is ambiguous. Please clarify what is an adequately long warming-up period.

Response: Thank you very much for your comment. Kim et al. (2018) suggested that different conceptual hydrological models require varying warming-up periods, which may be influenced by factors such as model structure. Their testing showed that when the warming-up periods for the two conceptual models, HYMOD and IHACRES, were

set to 1.5 months and 6 months respectively, the initial condition no longer had a significant impact on the results. In our study, the daily simulation began on February 10, 2014. Testing revealed that even under extreme conditions where the initial soil moisture is set to 0 or fully saturated, there is almost no impact on the flood simulation results (see Table R1). This indicates that by the time of flood onset, the state variables of the hydrological model had either stabilized. Since the duration of the warm-up period for testing is beyond the scope of our study, we only briefly mention the test and its results in the revised manuscript (Lines 371-376).

	Relative error of flood peaks			NSE			
Serial	Zero	Saturated	Half-	Zero	Saturated	Half-	
number	initial	initial	saturated	initial	initial	saturated	
	values	values	initial values	values	values	initial values	
2014052300	0	0	0	0.85	0.86	0.86	
2014070300	-0.05	-0.05	-0.05	0.95	0.95	0.95	
2014071400	0	0	0	0.94	0.94	0.94	
2015060121	-0.04	-0.04	-0.04	0.93	0.93	0.93	
2015060718	-0.08	-0.08	-0.08	0.83	0.83	0.83	
2015062023	-0.12	-0.12	-0.12	0.95	0.95	0.95	
2016050703	-0.07	-0.07	-0.07	0.91	0.91	0.91	
2016062017	-0.18	-0.18	-0.18	0.72	0.72	0.72	
2016062720	-0.13	-0.13	-0.13	0.87	0.87	0.87	
2016070311	-0.06	-0.06	-0.06	0.97	0.97	0.97	
2017052208	0.01	0.01	0.01	0.89	0.89	0.89	
2017062711	0	0	0	0.94	0.94	0.94	
2017081121	0.14	0.14	0.14	0.66	0.66	0.66	
2018053010	0.02	0.02	0.02	0.92	0.92	0.92	
2018092518	-0.12	-0.12	-0.12	0.83	0.83	0.83	
2019051905	-0.06	-0.06	-0.06	0.94	0.94	0.94	
2019070700	-0.05	-0.05	-0.05	0.96	0.96	0.96	
2020070800	-0.10	-0.1	-0.10	0.87	0.87	0.87	
2020071823	-0.17	-0.17	-0.17	0.86	0.86	0.86	
2020091500	-0.02	-0.02	-0.02	0.96	0.96	0.96	
2021050300	0.05	0.05	0.05	0.54	0.54	0.54	
2021051112	-0.07	-0.07	-0.07	0.89	0.89	0.89	
2021060300	-0.08	-0.08	-0.08	0.82	0.82	0.82	
2023040308	0.27	0.27	0.27	0.45	0.45	0.45	
2023050416	-0.11	-0.11	-0.11	0.64	0.64	0.64	
2023052008	0.36	0.36	0.36	0.70	0.70	0.70	
2023062100	-0.16	-0.16	-0.16	0.86	0.86	0.86	
2023063000	-0.16	-0.16	-0.16	0.55	0.55	0.55	
2023072516	-0.10	-0.10	-0.10	0.87	0.87	0.87	

Table R1. Flood simulation results for different daily simulation initial conditions

	Relative error of flood peaks			NSE			
Serial	Zero	Saturated	Half-		Zero	Saturated	Half-
number	initial	initial	saturated		initial	initial	saturated
	values	values	initial values		values	values	initial values
2024040100	0.16	0.16	0.16		0.47	0.47	0.47
2024042900	0	0	0		0.69	0.69	0.69

Revised Manuscript LINES 371-376:

As long as the warming-up period is adequately long, the influence of initial soil moisture on the daily simulation becomes minimal by the end of warming-up period, allowing soil moisture for daily simulation to be used as initial conditions for hourly simulation (Yao et al., 2012). The daily simulation in this study began on February 10, 2014. Testing showed that even in extreme cases where the initial soil moisture in the daily simulation is set to zero or fully saturated, there is almost no impact on the flood simulation results. So, they can be set arbitrarily within reason.

3. LT = 8 hours. Please comment on how useful it is in real world applications, for example, is it sufficient for issuing flood warning and mobilising rescue resources within 8 hours?

Response: Thank you for your helpful suggestion. The average time interval between the onset of the main rainfall event and the peak flow at the basin outlet is approximately 7 hours in study catchment. Therefore, we set the maximum lead time to 8 hours, slightly longer than this interval. This choice is supported by several reasons:

(1) This lead time meets the requirements for real-time flood forecasting in mediumsized basins. Real-time flood forecasting is a dynamic prediction system based on realtime monitoring data, combined with hydrological and/or hydrodynamic models, to forecast the development of flood events. It provides essential information such as the timing of peak flows, water levels, and discharge when flooding occurs. Due to its high timeliness and short forecasting window, the lead time is generally set to a few hours (e.g., Toth et al., 2000; Liu et al., 2016). The method proposed in this study is particularly suited for real-time updating in real-time flood forecasting, where it dynamically updates the hydrological model's state variables based on real-time observational data. Our approach can provide reliable real-time and near real-time information for emergency responses, assisting governments and relevant flood control agencies in managing evacuations, resource allocation, reservoir operations, and other disaster mitigation efforts, thereby minimizing casualties and property losses caused by floods. (2) Some researchers have identified that the accumulation of errors in the state variables of hydrological models is the main source of uncertainty during the initial phase and near real-time forecasting period (Weerts et al., 2006). However, as the lead time extends, the uncertainty in numerical weather predictions increasingly dominates and becomes the primary factor affecting flood forecasting accuracy (Yossef et al., 2013; Thiboult et al., 2016). The aim of this study is to reduce the accumulated error in hydrological model state variables at the start of the forecast. By setting a relatively short lead time, the error accumulation in state variables remains the key factor influencing flood forecast accuracy. In medium- and long-term flood forecasting, however, the uncertainties from numerical weather predictions may take precedence, which lies beyond the scope of our study.

We have added a discussion on the lead time in the discussion section of the revised manuscript (Lines 682-697).

Revised Manuscript LINES 682-697:

Real-time flood forecasting is a dynamic prediction system based on real-time monitoring data, combined with hydrological and/or hydrodynamic models, to predict the evolution of flood processes. It provides critical information such as the time of peak flow, water levels, and discharge when a flood occurs. This type of forecasting is characterized by its high timeliness and short forecasting window, with the lead time generally set to several hours (e.g., Toth et al., 2000; Liu et al., 2016). The methods proposed in this study is particularly suited for state updating within real-time flood forecasting, as it dynamically updates the state variables of the hydrological model using real-time observational data, reducing the accumulation of errors. In real-world cases, we set the maximum lead time to 8 hours, which sufficiently meets the requirements for real-time flood forecasting in medium-sized catchments. This provides reliable real-time and near-real-time information for emergency responses, assisting government and flood control agencies in organizing evacuations, resource allocation, and reservoir operations, thereby minimizing casualties and property damage caused by floods. Moreover, to test the temporal persistence of the state updating method, we used historical observed rainfall as a perfect proxy for numerical weather forecasts, thereby avoiding the introduction of uncertainties from numerical weather predictions. As the lead time increases, uncertainties in numerical weather predictions may gradually replace the accumulation of errors in hydrological model state variables as the primary source of uncertainty in flood forecasting (Weerts et al., 2006; Yossef et al., 2013; Thiboult et al., 2016). For medium- to long-term flood forecasts, greater attention may need to be given to uncertainties stemming from numerical weather predictions.

Reference mentioned in our responses

- Kim, K. B., Kwon, H. H., and Han, D. W.: Exploration of warm-up period in conceptual hydrological modelling, J. Hydrol., 556, 194-210, https://doi.org/10.1016/j.jhydrol.2017.11.015, 2018.
- Liu, Z., Guo, S., Zhang, H., Liu, D., and Yang, G.: Comparative study of three updating procedures for real-time flood forecasting, Water Resour. Manag., 30, 2111-2126. https://doi.org/10.1007/s11269-016-1275-0, 2016.
- Thiboult, A., Anctil, F., and Boucher, M. A.: Accounting for three sources of uncertainty in ensemble hydrological forecasting, Hydrol. Earth Syst. Sci., 20, 1809-1825, https://doi.org/10.5194/hess-20-1809-2016, 2016.
- Toth, E., Brath, A., and Montanari, A.: Comparison of short-term rainfall prediction models for real-time flood forecasting, J. Hydrol., 239(1-4), 132-147. https://doi.org/10.1016/S0022-1694(00)00344-9, 2000.
- Weerts, A. H. and El Serafy, G. Y. H.: Particle filtering and ensemble Kalman filtering for state updating with hydrological conceptual rainfall-runoff models, Water Resour. Res., 42, W09403, https://doi.org/10.1029/2005WR004093, 2006.
- Yossef, N. C., Winsemius, H., Weerts, A. H., van Beek, R., and Bierkens, M. F. P.: Skill of a global seasonal streamflow forecasting system, relative roles of initial conditions and meteorological forcing, Water Resour. Res., 49, 4687-4699, https://doi.org/10.1002/wrcr.20350, 2013.